Examining the Determinants of Abnormal Return Volatility During Seasoned Equity Offerings

A thesis submitted in fulfilment of the requirements for the degree of

Doctor of Philosophy at Western Sydney University

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	Western Sydney University
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Acknowledgements

Martin Luther King Jr said, “Somewhere along the way, we must learn that there is nothing greater than to do something for others.” Throughout the process of writing this thesis, I have reminded myself of this phrase to persevere through challenges, with the goal of sharing my research to benefit others.

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Statement of Authentication

I, Mason Prasad, acknowledge that this thesis contains no material which has been accepted for the award of any other degree and that, to the best of my knowledge and belief, this thesis contains no material previously published or written by another person, except where due reference is made within the text of the thesis.

Signature of Applicant

[redacted]…

10th August 2022

Declarations

This thesis has been prepared to meet the requirements of a Doctor of Philosophy degree at Western Sydney University.

I declare that this thesis represents my work, except where due acknowledgement is made, and it has not been previously included in a thesis, dissertation or report submitted to this University or to any other institution for the award of a degree, diploma or other qualification.

I declare that this thesis has undergone professional editing by Elite Editing Australia. The editorial intervention was restricted to Standards D and E of the *Australian Standards for Editing Practice*. This means that the professional editor has not made alterations to the content of my work. All possible care has been taken in the preparation of the information in this thesis; however, I expressly disclaim any liability for the accuracy and sufficiency of the information and under no circumstances shall either be liable in negligence or otherwise in and arising out of the preparation or supply of the information in this thesis.

Preface

The research in this thesis was undertaken by the candidate at Western Sydney University in the School of Business, under the supervision of Associate Professor Maria Estela Varua and Dr Walid Bakry from February 2019 to August 2022.

The integrity of this PhD thesis has been validated by the following publication:

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List of Abbreviations

ADF	Augmented Dickey–Fuller
ASIC	Australian Securities and Investments Commission
ASX	Australian Securities Exchange
DRP	Dividend reinvestment plan
GARCH	Generalised autoregressive conditional heteroscedasticity
GJR	Glosten–Jagannathan–Runkle
GFC	Global Financial Crisis
GICS	Global Industry Classification Standard
IPO	Initial public offering
MLR	Multinomial logistic regression
RQ	Research question
SEO	Seasoned equity offering
SPP	Share purchase plan
US	United States
AMV	Aggregate market volatility
ATR	Abnormal turnover ratio
AVAR	Average abnormal return
AVOL	Abnormal trading volume
BAS	Bid–ask spread
CIT	Corporate insider trading
COE	Cost of equity
DIS	Economic disruptions
DISC	SEO discount

EPS	Earnings per share
ILLIQ	Stock illiquidity
LIQ	Amivest liquidity ratio
MBV	Market-to-book value
MSAD	Market-sensitive announcements
RRR	Relative risk ratio
SD	Standard deviation
SIZE	Firm size

Abstract

Over the past few decades, firms in major international markets, including Australia, the United Kingdom, Hong Kong, the United States and Canada, have displayed a growing preference for equity financing through seasoned equity offerings (SEOs) in place of debt financing. Notably, the Australian market is among those that have experienced the most prolific issuances of SEOs because of the quick turnaround time, the freedom to choose the amount of capital to be raised and the control over the issuance price of SEOs. These benefits are some of the many reasons that SEOs have been favoured by firms as the primary mechanism for raising capital, particularly during periods of economic disruption. Given that the popularity of SEOs has increased exponentially among Australian Securities Exchange (ASX) listed firms, it is imperative that these firms also consider the effects of their SEO decision on their shareholders, from the perspective of return volatility. Return volatility is important to shareholders for it is among the most widely used metric to assess investment risk. During SEO announcements, the level of shareholder trading activity typically increases, which may transform normal levels of return volatility into abnormal levels. The increase in abnormal return volatility increases risk and may have negative consequences on a shareholder’s portfolio.

Unfortunately, very few studies have examined the relationship between SEOs and abnormal return volatility, which presents a research gap. Specifically, firms are unaware about the SEO types that induce abnormal return volatility and therefore will be unable to decide on the most appropriate type. To date, a firm’s main consideration is to choose an SEO type that will help it satisfy their capital needs, and thus, it disregards the likely impact of this decision on its existing shareholders. Hence, this thesis seeks to address this gap in the literature by providing a framework to help firms make SEO decisions that are more considerate to their shareholders. To achieve this goal, an event study methodology is employed to verify the presence of

abnormal return volatility within ASX 200 firms in 1998–2020, by using multiple proxies. The traditional proxy for abnormal return volatility (*AVAR*) is used as a baseline measure to confirm the presence of abnormal return volatility. Then, the accuracy of this traditional proxy is improved to form two additional proxies by incorporating the stylised features of stock return volatility, that is, leptokurtosis, heteroscedasticity and volatility clustering. This is accomplished by using a generalised autoregressive conditional heteroscedasticity (GARCH) and Glosten–Jagannathan–Runkle–GARCH (GJR–GARCH) specification to replace the variance component of the traditional *AVAR* proxy, resulting in two new proxies: *AVAR–GARCH* and *AVAR–GJR–GARCH*. The event study results confirm not only that abnormal return volatility is present during SEO announcements in the aggregate market with variations occurring across each SEO type and sector, but also that the *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies are more accurate measures of abnormal return volatility. Further, the findings highlight that abnormal return volatility tends to be higher during periods of economic disruption (i.e. the early 2000s dot-com bubble, the 2008 Global Financial Crisis and the 2020 coronavirus disease, or COVID-19, pandemic), than in the entire sample period.

After identifying abnormal return volatility (based on the improved proxies, *AVAR–GARCH* and *AVAR–GJR–GARCH*), these proxies are used as the dependant variable in a multinomial logistic regression on panel data to examine its determinants. The regression results provide compelling evidence to suggest that a combination of determinants instigates low, moderate or high levels of abnormal return volatility across each the aggregate market and, by extension, in specific SEO types and sectors. In line with these results, a set of recommendations are provided to help firms identify the most ideal SEO type that helps reduce the negative effect on their shareholders, depending on the economic period. The results indicate that across the entire sample period, placement & share purchase plans and the standalone non-renounceable rights issues were the most ideal SEO types to use for equity raising. However, during economic disruptions, firms should ideally use either the standalone private placement or the placement & renounceable rights issue (if they wish to ensure they include institutional as well as retail shareholders in the SEO). The results also highlight that across the entire sample period, Health Care, Real Estate and Industrials were high-risk sectors. Therefore, firms in these sectors would benefit by aligning their SEO choices to the ideal SEO types. Moreover, during economic disruptions, in addition to these three sectors, the Information Technology sector is classified as a high-risk sector. These results highlight that firms in these sectors should exercise additional care to ensure that they choose an SEO type that is associated with either no or lower levels of abnormal return volatility.

Overall, this thesis demonstrates that the SEO type and the sector in which a firm operates will both have a significant effect on abnormal return volatility during SEO announcements, which needs to be addressed. It highlights that some SEO types are more appropriate to use in general but may not necessarily be as appropriate specifically during economic disruption periods. Thus, the results of this thesis provide equity-raising firms with a framework to support the SEO decision-making process towards minimising the abnormal return volatility experienced by their shareholders. This framework also provides capital market regulators the means to undertake regulatory reforms towards improving the transparency of ASX-listed firms during SEOs. Using the insights that this thesis provides, firms should take the necessary steps to minimise their contribution to abnormal return volatility during SEOs, which will ultimately enhance investor confidence and help improve their future equity-raising prospects.

Chapter 1: Introduction

1.1 Background

Australian Securities Exchange (ASX) listed firms are well known for their ability to flourish during economic expansions and endure periods of economic uncertainty, remaining relatively unscathed. This resilience is largely attributable to these firms' ability to raise external capital from investors whenever required. In Australia, ASX-listed firms can use two types of external capital raising, namely, debt financing and equity financing. Debt financing involves firms issuing short-term (e.g. convertible notes) or long-term debt (e.g. corporate bonds) securities to investors and paying periodic coupon (interest) payments until maturity (Brailsford, Heaney & Bilson 2011). In some circumstances, firms can issue zero-coupon debt securities, which do not offer coupon payments but instead trade at a large discount, rendering a realised profit for the holder on maturity (Brailsford, Heaney & Bilson 2011). The second type, equity financing, refers to the process of raising capital through selling shares to the public or to a select group of investors (Brailsford, Heaney & Bilson 2011). Since debt financing is the cheaper of the two options, it has traditionally been the more popular choice among firms than equity financing (Hall 2002).

Nevertheless, despite the lower issuance costs of debt financing, since the early 2000s ASX-listed firms have increasingly preferred equity financing in the form of seasoned equity offerings (SEOs) to fund their operations. An SEO is a capital-raising instrument that allows a publicly listed firm to obtain funding through issuing shares multiple times after its initial public offering (IPO).[1] The main drivers of this trend include the faster turnaround times of SEOs, the freedom that firms possess to choose the amount of capital they wish to raise and their ability to oversee the SEO issuance price (Papaioannou & Karagozoglu 2017). However most importantly, equity capital is available when firms need funds the most, namely, during periods of economic crisis, whereas debt is not easily available during such periods. During crises, banks are unlikely to allow firms to use bank loans as a source of capital due to of collapsing credit markets and immense financial uncertainty, which push lenders to either tighten their lending conditions or halt lending altogether (ASX 2010). Such a situation was experienced during the 2008 Global Financial Crisis (GFC) where there was a spike in credit spreads from an average of between 10 and 50 basis points in August 2007, to 100 basis points during the collapse of Lehman Brothers in September 2008 (ASX 2010). The observed spreads reflected illiquidity and heightened credit risk, which adversely affected firms' ability to obtain borrowed funds or use debt financing. Since then, the popularity of the SEO has increased sharply, and it is currently more popular than ever. The remainder of this chapter proceeds as follows. Section 1.2 discusses the growth of SEOs in Australia, and Section 1.3 presents the research gap and contributions. Section 1.4 covers the five overarching research questions, followed by Section 1.5 which presents the research objectives. Section 1.6 outlines the research methodology followed by Section 1.7 which concludes the chapter.

1.2 Growth of Seasoned Equity Offerings in Australia

The dividend imputation system, which was introduced in 1987, drove the increasing use of SEOs by Australian firms which resulted in Australia's inclusion among countries with the largest number of SEOs (ASX 2010; McLean, Zhang & Zhao 2008). As shown in Figure 1.1,

[1] An IPO is when a firm raises capital from the public for the first time through listing on a public exchange. During the nascent stages of going public, firms typically obtain privately funded capital to kick start the start-up process (Jain & Kini 1999). The benefits obtained from going public is that it allows firms to raise capital in two forms: debt and equity.

SEOs became increasingly popular from 1995 to 2009, and experienced a faster growth rate than IPOs. A comparison of IPOs and SEOs shows that the amount of capital raised from IPOs averaged AUD9.8 billion per year, and the smallest amount was raised during the GFC in 2008 (AUD2.5 billion). The second smallest amount of capital was raised during the early 2000's (specifically 2001), which highlights the depleting interest of firms to undertake IPOs. This is likely due to the economy experiencing the bursting of the tech bubble during the early 2000's. This resulted in a disincentive for new firms to list on the ASX due to the heightened risk of being unable to raise sufficient capital to support the IPO (Steen & Murray 2013). In contrast, during the same period, the total capital raised from SEOs was almost three times more (AUD30 billion per year), and a record amount of AUD98.6 billion was raised during the recovery in 2009 (Australian Securities and Investments Commission [ASIC] 2020a; ASX 2010). Similarly, during the pandemic caused by the coronavirus disease (COVID-19), ASX-listed firms continued this strong reliance on SEOs in 2020 and 2021 through raising AUD66 billion and AUD60 billion, respectively (Thomson Reuters Practical Law 2022).

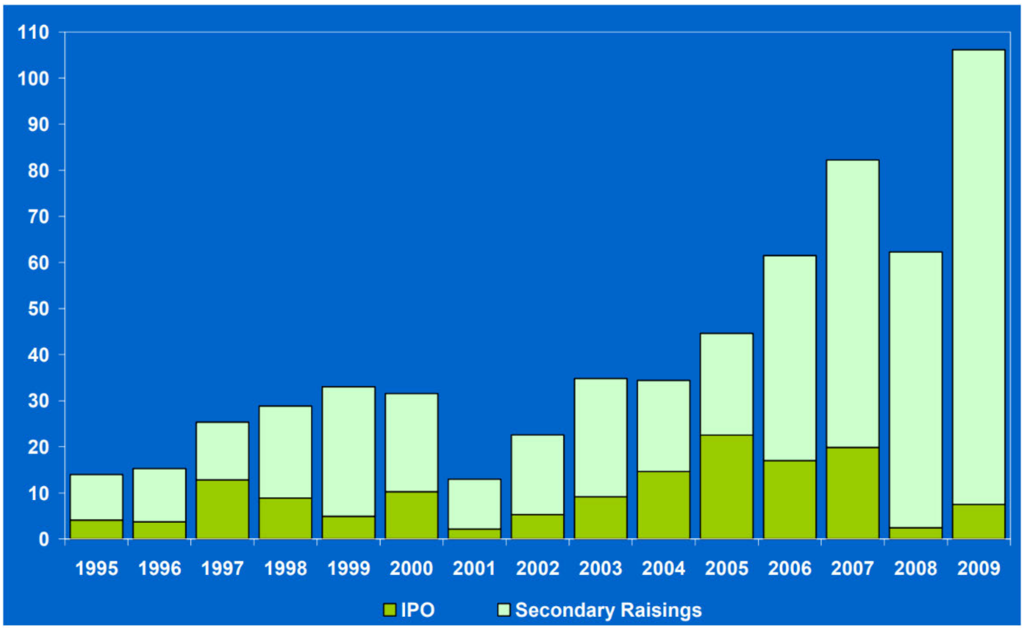

Figure 1.1: Australian Capital Raised (IPOs v. SEOs) (AUD in billion; source: ASX 2010)

Australian firms' ability to successfully and quickly raise equity demonstrates their strength and resilience in financial markets. Market makers, including the ASX, and capital regulators, such as the ASIC, have also supported the use of SEOs. Their support was evident during periods of economic disruptions wherein these entities temporarily eased capital requirements. Such initiatives allowed the equity-raising process to be expedited for firms wishing to use SEOs. Although this process allowed *firms* to prosper in the Australian financial market, it did not benefit all shareholders equally. This disparity was evident during the GFC, during which private placement funding limits were temporarily increased from 15% to 25%, allowing firms to raise larger-than-normal levels of capital to continue their operations during economic uncertainty (ASX 2010). This measure resulted in a surge in the use of private placements during the GFC period, particularly by firms in the Financials sector (ASX 2010). In this case, when a firm chose to undergo a private placement, it engaged only with institutional shareholders (e.g. investment banks and hedge funds), resulting in the exclusion of its existing retail shareholders from the SEO. Moreover, institutional shareholders' purchase of large parcels of shares intensified the extent of stock ownership dilution experienced by retail shareholders.

Thus, the ASIC was faced with the task of deciding on a fair way to allow firms to continue raising capital (using private placements) while minimising the dilutive impact on existing retail shareholders. It addressed this concern when the financial markets tumbled during the COVID-19 pandemic in March 2020 by mandating the offer of a share purchase plan (SPP) for existing retail shareholders by firms that wanted to issue a private placement (ASX 2020a). Other supportive measures that were implemented include the ASX temporarily removing the 1-for-1 limit on non-renounceable rights in April 2020 for three months. This proved to be an effective method for maximising a firm's equity-raising prospects during times when it most needed financial support and, simultaneously, ensuring fairness for institutional as well as retail shareholders. In recognition of the benefits obtained by firms and their shareholders from SEOs, the expiration date of these relaxed rules was extended from July 2020 to 30 November 2020 (ASX 2020a). These supportive and equitable capital-raising initiatives have enabled ASX listed firms to be one of the most robust among international financial markets, particularly during periods of economic disruption. Nevertheless, the use of SEOs can increase the levels of stock return volatility, which may make participation in SEOs a risky investment decision for existing shareholders (Bae & Jo 1999; Hibbert et al. 2020; Ho et al. 2005).

Stock return volatility has been a critical risk management metric, which dates to Fama's (1965, 1970) early research focused on the efficient market hypothesis. According to this hypothesis, an efficient market reflects all available financial and non-financial information in current stock prices, and therefore, financial markets should not experience high levels of volatility. However, practitioners have proven repeatedly that financial markets do exhibit excessive levels of volatility in response to information disclosures by firms, which goes against the assumptions of the strong-form efficient market hypothesis (Beechey, Gruen & Vickery 2000; Naseer & Bin Tariq 2015; Rossi 2015; Rossi & Gunardi 2018). A phenomenon highlighted by Mandelbrot (1963) and Fama (1965) is that volatility in financial asset returns exhibits a clustering behaviour; that is, large (small) changes in a firm's stock price during one period are usually followed by large (small) changes in the subsequent period. This behaviour suggests that the volatility in each period is interrelated, which opened the door to numerous studies on the behaviour of volatility clustering (Bentes, Menezes & Mendes 2008; Cont 2007; Tseng & Li 2011). Various studies have shown that a firm's stock price exhibits the same behaviour during SEO announcements, which suggests that there is volatility clustering during SEOs also, arising from the price swings that occur before and after an SEO announcement (Bae & Jo 1999; Hibbert et al. 2020; Ho et al. 2005). Masulis and Korwar (1986) reported that pre-announcement price swings occur owing to the large price run-up caused by insiders trading on private information. After the SEO announcement, the share price usually drops significantly, which is consistent with the overvaluation hypothesis (Myers & Majluf 1984). Consequently, the ongoing swings occurring in the stock price each time a firm undertakes an SEO result in increased stock return volatility, which can lead to long-term underperformance of the firm's shares (Myers & Majluf 1984). In some cases, if a firm undertakes multiple SEOs in periods of deteriorating market sentiment or chooses a particular SEO type that favours institutional shareholders over retail shareholders, this act may translate normal or expected levels of return volatility into *abnormal* levels, which can adversely affect shareholder returns. The phenomenon of abnormal return volatility is present in earnings announcements across international markets (Khan et al. 2015; Landsman & Maydew 2002; Landsman, Maydew & Thornock 2012; Lin, KJ, Karim & Carter 2014; Truong 2012). Therefore, it is reasonable to expect that when firms announce that they will be undertaking an SEO, abnormal return volatility will occur since these SEOs are typically used to help grow the *earnings* of the firm.

In summary, since Australian firms are prolific issuers of SEOs, they are expected to continue using SEOs to support their ongoing growth and survival. Thus, it is reasonable to assume that the associated volatility will continue to be a natural part of the SEO issuance process. If the stock return volatility levels exceed the norm, firms must take action. Abnormal levels of volatility can significantly harm investors' portfolios, making it crucial for firms to address this concern. Moreover, if firms leave abnormal return volatility unaddressed during SEOs, it is likely to deter investors from participating in future equity-raising rounds, which may hinder a firm's equity-raising prospects. The following subsection highlights the research gaps in the literature with regards to abnormal return volatility during SEOs and the contributions of this thesis towards addressing these gaps.

1.3 Research Gap and Research Contributions

1.3.1 Research Gap

The increasing popularity of SEOs as a means of raising capital has led to increasing research into its effect on equity markets. However, the literature on abnormal return volatility during SEOs is sparse, particularly in the context of the Australian market. This key gap in the body of literature is the focal point of this research. Since 1984, the literature has documented the reasons underlying firms' reliance on SEOs and their impact on stock returns across international markets (Asquith & Mullins 1986; Baker & Wurgler 2002; Brav & Gompers 1997; Chen, S 2017; Hovakimian, Opler & Titman 2001; Jegadeesh 2000; Jung, Kim & Stulz 1996; Liu et al. 2016; Loughran & Ritter 1995; Korajczyk, Lucas & McDonald 1991; Murgulov 2006; Myers & Majluf 1984; Ritter 1991; Speiss & Affleck-Graves 1995). In this literature, three notable studies (Bae & Jo 1999; Hibbert et al. 2020; Ho et al. 2005) examined the volatility of stock returns during SEOs across the United States (US) and Taiwanese markets. Interestingly, despite the Australian market ranking second worldwide in terms of the number of SEOs issued, no studies have examined the effect of SEO announcements on stock return volatility in this market. Since firms in the Australian market are prolific issuers of SEOs, it reasonable to expect that they will continue to issue them to service their ongoing capital needs. Therefore, it is also reasonable to expect that the associated volatility will continue to be part of the SEO decision. However, if these decisions elicit abnormal levels of stock return volatility, this can be of concern to a firm's shareholders because it may deter them from participating in the SEO and hinder the firm's ability to satisfy its capital requirements.

In this regard, SEOs can provide a sufficient amount of capital, and there are various uniquely structured SEO types that differ in terms of the rights, restrictions and opportunities available to institutional and retail shareholders. Moreover, the ASX has stipulated that Australian firms should choose the SEO type that helps them raise equity as quickly as possible, particularly during economic disruptions. For example, an inquiry into the Australian financial system in 2014 reported that during the 2008 GFC, Australian firms gravitated towards private placements as their SEO type of choice because it has the quickest turnaround time (3–4 business days). Unfortunately, these private placements diluted the ownership percentage of retail shareholders by more than 30%, or approximately AUD10 billion. This dilution occurred because private placement limits were eased, shares were offered only to institutional shareholders and no follow-up SPP was offered to retail shareholders. Other disadvantages experienced by retail shareholders included intentionally poor marketing of retail offers, rights issues not being issued with a renounceability option, and limits on the opportunity to apply for additional shares in rights issues. These inequitable conditions instigated high levels of stock return volatility, which shook investor confidence (Connal & Lawrence 2010). Further, since each SEO type has a unique structure, it is expected they each type will instigate varied shareholder reactions, some of which may instigate low levels of return volatility whereas others may instigate abnormal return volatility.

During the 2008 GFC, shareholders of ASX-listed firms experienced the negative effects of SEO-induced abnormal return volatility, an issue that market makers and regulators unfortunately did not address then. During COVID-19, however, the ASX and the ASIC were more vigilant in recognising these negative effects and attempted to address the excessive levels of return volatility experienced by retail shareholders by attaching a caveat to the eased private placement limits. The caveat required that if ASX-listed firms chose to undertake a private placement, it was mandatory to also include a follow-up SPP for retail shareholders. This caveat was enforced to ensure that institutional and retail shareholders were both provided with an equal opportunity to participate in the SEO (ASX 2020a). Nevertheless, despite these improvements based on the lessons learned from the GFC, firms still experienced abnormal levels of volatility when issuing SEOs during the COVID-19 pandemic. Thus, the fact that excessive levels of volatility still play a significant role during SEOs, despite institutional and retail shareholders being fairly treated, warrants further investigation into the SEO-specific, firm-specific and market-wide determinants that elicit abnormal return volatility across each SEO type and into any variations across sectors. This thesis places high importance on providing insights that would facilitate a firm in choosing an *appropriate* SEO to help minimise their contribution to abnormal return volatility. Failure to choose an appropriate SEO type may negatively influence shareholder confidence and therefore hinder a firm's ability to raise equity in the future (Chen, Chou & Lin 2019; Chou & Lin 2015).

Various competing theories attempt to explain the optimal capital structure that firms adopt to foster their ongoing growth in capital markets. The most common theories of capital structure include the trade-off theory (Kraus & Litzenberger 1973), pecking order theory (Donaldson 1961), adverse selection theory (Myers & Majluf 1984) and the market timing theory (Baker & Wurgler 2002). The *market-timing theory* and *adverse selection theory* are utilised as the theoretical foundations of this thesis as they provide an explanation for why firms favour equity raising over other capital raising methods. Baker and Wurgler's (2002) market-timing theory asserts that market timing is a firm's most important consideration when deciding to issue equity. The theory suggests that firms can capitalise on an inefficient capital market and information asymmetry by timing a share issue to their benefit. Specifically, a firm can increase the chance of a successful SEO when its share price is overvalued relative to its book value. In a similar vein, Myers & Majluf's (1984) adverse selection theory focuses specifically on the *timing* of equity issuances via SEOs. This theory posits that managers take advantage of periods of overvaluation to issue equity based on the superior information they have regarding the value of their firm. These theories highlight that the SEO announcement is typically followed by a sharp negative stock price reaction as investors absorb the new information (Murgulov 2006).

It is in the days surrounding this announcement that this thesis expects abnormal levels of stock return volatility to occur.

1.3.2 Significance of the Study

Following from the discussion in the previous sections, this thesis provides four contributions to the existing literature. *First*, it examines and measures the extent to which SEOs instigate and perpetuate abnormal return volatility, a topic that the literature is yet to cover. To achieve this, it employs an event study methodology, using the traditional abnormal return volatility (*AVAR*) proxy as a measure to confirm whether there is abnormal return volatility in ASX 200 firms' share prices during SEO announcements. Capturing this type of shareholder reaction is an important metric that firms can use to understand how their shareholders react to specific SEO types and to adjust their decision accordingly. It is also important to provide regulators and market makers with a framework to inform policy decisions about choosing an appropriate SEO type to guide the equity raising decision-making process. As previously mentioned in section 1.2, the large volume of equity raising undertaken by ASX-listed firms can result from multiple equity-raising rounds during their lifetime. Consequently, these decisions will also affect their investors on multiple occasions during the period of their investment, and with each subsequent SEO, investors' exposure to abnormal return volatility will increase (Asquith & Mullins 1986; Chen, Chollete & Ray 2010; Nelson 1991).

The *second* contribution of this thesis is that it improves the existing *AVAR* proxy. It does so by integrating generalised autoregressive conditional heteroscedasticity (GARCH) and the Glosten, Jagannathan and Runkle (1993) GARCH (GJR–GARCH) effects within the *AVAR* proxy to provide two improved proxies: *AVAR–GARCH* and *AVAR–GJR–GARCH*. The limitation of the traditional *AVAR* proxy is that it uses a standard measure of variance, which assumes that each period's variance is independent. However, stock returns exhibit volatility clustering, whereby the current period's variance is not independent but is instead influenced by that of the previous period (Mandelbrot 1963; Tsay 1987). Unlike the traditional *AVAR* measure, the GARCH specification captures this phenomenon by using conditional variance instead of the standard variance measure. Moreover, GARCH-based proxies also account for other common stylised features of stock return volatility (heteroscedasticity and a leptokurtic distribution), which further validates the appropriateness of the GARCH specification in the *AVAR–GARCH* proxy. In addition, the *AVAR–GJR–GARCH* measure incorporates the leverage effect, which provides robustness to the GARCH specification (Glosten, Jagannathan & Runkle 1993). Thus, this research is timely, considering that no prior studies have measured investor reactions to SEOs for the Australian market, or in any other market, in such a manner.

Third, this thesis challenges the assumption that all SEO types elicit a homogeneous impact on return volatility within the Australian market. It does so by examining the abnormal return volatility for *each SEO type* and its determinates to ascertain their idiosyncratic impact on abnormal return volatility. As previously mentioned, since each SEO type provides institutional and retail shareholders with varying levels of rights and opportunities, the degree of shareholder reactions to each SEO type likely varies (Liu et al. 2016).

Fourth, this thesis examines the effect of each SEO announcement on abnormal return volatility on a sectoral basis as well as its effect on the aggregate market. The purpose of this disaggregation is to account for the distinct 'two-speed' Australian economy, which consists of high- and low-performing sectors (Alam, Wei & Wahid 2020; Deo, Spong & Varua 2017). Therefore, it is expected that both types of sectors will experience different reactions to SEO announcements.

As mentioned previously, this thesis also focuses on three economic disruptions because they are characterised as periods of higher economic uncertainty and therefore higher volatility. The aforementioned contributions will provide further knowledge to market participants on SEOs and their behaviour, particularly for ASX-listed firms. The insights gained will help to guide firms in choosing the most appropriate SEO type to reduce abnormal return volatility. It will also provide firms with knowledge about whether the SEO decision should be incorporated into their equity-raising risk-assessment process.

1.4 Research Questions

Five overarching research questions (RQs) are defined in this study, which will help to address the gaps identified in the literature:

RQ1: Is there a significant increase in abnormal return volatility across the aggregate market during periods of economic disruption compared with the entire sample period and what are its determinants?

RQ2: Which SEO types exhibit higher and lower levels of abnormal return volatility during SEO announcements?

RQ3: What are the determinants of the abnormal return volatility for each SEO type?

RQ4: Which Australian sectors exhibit abnormal return volatility in response to SEO announcements and is this exacerbated during economic disruptions?

RQ5: What are the determinants of the abnormal return volatility found across each Australian sector?

1.5 Research Objectives

The main objective of this thesis is to confirm the presence and examine the determinants of abnormal return volatility for each SEO type issued in the Australian financial market. To address the research questions specified in Section 1.4, the following research objectives have been identified:

1. Analyse the extent to which abnormal return volatility occurs in standalone, restricted and combined SEO types.
2. Identify the extent to which abnormal return volatility transpires in each Australian sector by highlighting similarities and differences in high-, moderate- and low-performing sectors.
3. Examine the degree to which abnormal return volatility changed during economic disruptions compared with the entire sample period.
4. Ascertain and evaluate the hypothesised determinants of the abnormal return volatility for each SEO type and sector in order to provide tailored SEO recommendations to firms.

1.6 Research Methodology

As shown in Figure 1.2, the research methodology is implemented in two phases. In the first phase, the traditional abnormal return volatility proxy, *AVAR*, is improved upon to account for volatility clustering, which yields two new proxies (*AVAR–GARCH* and *AVAR–GJR–GARCH*). All three proxies are calculated for each day of the SEO event window [−15, +15] using an event study methodology. Last, the results from the new proxies are compared with those of the traditional AVAR proxy to determine the difference in the extent of abnormal return volatility as measured by these proxies. In the second phase, multinomial logistic regression (MLR) modelling is used to examine the SEO-specific, firm-specific and market-wide determinants of abnormal return volatility. Both phases are employed for the aggregate market (refer to Chapter 5), each SEO type (refer to Chapter 6) and each sector (refer to Chapter 7).

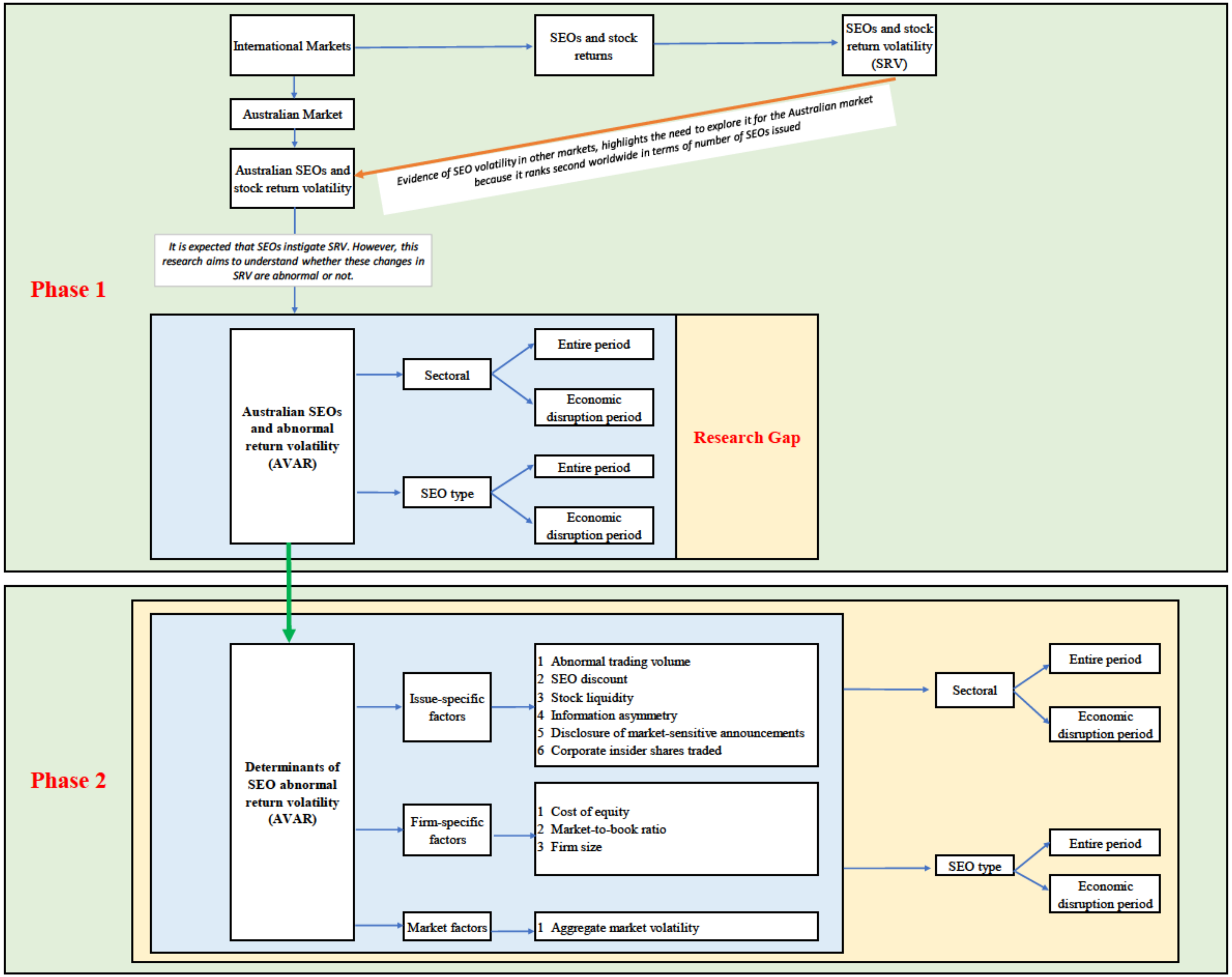

Figure 1.2: Summary of Research Methodology

1.7 Summary of Thesis

This thesis examines the presence and determinants of abnormal return volatility during SEOs issued by Australian listed firms. As previously highlighted, Australian firms are among the most prolific issues of SEOs in the world, and thus, abnormal return volatility during SEO announcements is an important risk consideration for both the shareholder and the equity-raising firm. Hence, this study provides knowledge to market participants about abnormal return volatility during SEOs as well as the contributing factors, which firms can use for making more effective SEO decisions. Following on from this introductory chapter, this thesis consists of a further seven chapters.

Chapter 2 provides an overview of the capital structure theories relevant to this thesis. This is followed by a discussion of the Australian SEO market and an explanation of the economic disruption periods covered by the thesis. Further, the trends of SEO issuances based on SEO type and sector are discussed to highlight firms' growing preference for SEOs. The advantages and drawbacks of each SEO type are also discussed, and justification is provided for the SEO types included in this study. Last, a critique of the role that regulators play, which also discusses the concerns that arise related to their responsibility to protect investors from excessive levels of volatility in financial markets, is undertaken.

Chapter 3 provides a detailed review of the existing literature on SEOs and on the reactions of market participants to SEO announcements. Further, a review of the literature on how abnormal return volatility is measured, along with a critique of the accuracy of the existing measure, is undertaken. Next, a discussion is presented on the independent variables likely to affect the abnormal return volatility of firms that undertake SEOs.

Chapter 4 describes the methodology and the data sources used in this thesis. The methodology is implemented in two phases. In Phase 1, tests are conducted to determine the presence of abnormal return volatility (*AVAR*) and two alternative abnormal return volatility proxies are proposed for capturing volatility clustering and other stylised features of financial asset return (leptokurtosis and heteroscedasticity). The alternate proxies employ GARCH and GJR–GARCH specifications to capture the conditional volatility of each firm around SEO announcements. In Phase 2, *AVAR–GARCH* and *AVAR–GJR–GARCH* are used as the dependant variables in an MLR modelling technique that explores the impact of a set of SEO-specific, firm-specific and market-wide determinants on abnormal return volatility. Two econometric models are employed to examine this relationship: Model 1 captures the effects for the whole sample period, whereas Model 2 captures the effects only for the economic disruption periods considered. With respect to the data sources, a discussion of the data points, the data collection methods and the selection criteria is presented.

Chapters 5, 6 and 7 present the results for Phases 1 and 2. In Chapter 5, a preliminary analysis is first undertaken to examine the nature of the data by employing unit root tests and multicollinearity tests. Next, the descriptive statistics of the dependant and independent variables are presented. The second half of Chapter 5 presents the results for Phases 1 and 2 for the aggregate market. In Chapters 6 and 7, the descriptive statistics, the Phase 1 results and the Phase 2 results are presented for the SEO types (Chapter 6) for each sector (Chapter 7). The implications of the results on firms and their shareholders are also discussed in these two chapters.

Chapter 8 concludes the thesis by presenting a summary of all the major findings. It also discusses the contributions and implications of the findings on firms and their shareholders. In addition, it provides recommendations for retail and institutional shareholders, portfolio managers and regulators based on the research findings with respect to each SEO type and each sector. Last, it discusses the limitations of this study and provides recommendations for further research.

Chapter 2: Overview of SEOs in Australia

2.1 Introduction

Chapter 2 provides an overview of the theoretical foundation of this thesis. The chapter starts with section 2.2 providing a summary of the theories related to firm capital structure that have evolved over time. Section 2.3 provides an overview of the Australian market landscape along with a discussion of the factors that have influenced the country's economic growth. Further, the economic disruption periods selected for this thesis and their origins are also presented. Section 2.4 discusses the growing trend in the uptake of seasoned equity offerings by ASX-listed firms, with a focus on the various SEO types used by firms and the SEO types most popular in each ASX sector. Section 2.5 explores each SEO type further with respect to their associated benefits and drawbacks. Finally, section 2.6 examines the role of regulators in the Australian SEO market and the measures implemented to help firms raise equity capital during economic periods of disruption.

2.2 Overview of Capital Structure Theories from 1958 to 2021

The theory of capital structure has been discussed numerous times since Modigliani and Miller's (1958) seminal research on the mix between debt and equity finance. Modigliani and Miller's (1958) theory of capital structure irrelevance on firm value assumes there is a perfect capital market, zero taxes, equal borrowing rates for businesses and individuals, zero liquidation/restructure costs for firms and a fixed investment policy. Subsequent research has challenged the validity of some of these assumptions, such as 'a world without taxes', which unquestionably exists. Moreover, firms that undertake debt financing can claim tax deductions on interest paid on debt, thus lowering the tax payable and increasing profitability, that is, improving firm value. These deductions ultimately make debt financing a cheaper option than equity financing. The challenging of these assumptions has influenced the development of alternative theories (with relaxed assumptions) to explain how real-world businesses are financed (Miller 1988). Examples of competing theories include the trade-off theory, the pecking order theory, the adverse selection theory and the market-timing theory, which are discussed next.

The first, the trade-off theory that Kraus and Litzenberger (1973) proposed, states that there is an optimal capital structure for debt, in which the cost of debt equals its benefits. Myers and Majluf (1984) showed that a firm trades-off the benefits of debt (i.e. tax savings) against its cost (i.e. dead-weight costs of bankruptcy). Another factor involved is agency costs, which arise from the conflict of interest between managers and investors (Jensen 1986; Jensen & Meckling 1976). This theory emphasises that debt financing has an advantage (i.e. tax savings) but also has an equal disadvantage (i.e. increased risk of bankruptcy). Firms therefore target their capital structure to achieve an optimal leverage ratio, which they constantly adjust when it deviates from the target.

The second, Donaldson’s (1961) pecking order theory, complements the trade-off theory but also includes the concept of asymmetric information. This theory states that the cost of financing increases as asymmetric information increases. Firms prioritise their sources of funding according to the level of asymmetric information, which directly affects the cost of financing. The theory states that firms opt to use internal funds first, followed by debt issuance once they exhaust their internal funds. Last, when the cost of debt becomes excessive or it is unavailable, firms use equity. Tests of the pecking order theory have presented mixed results. Zeidan, Galil and Shapir (2018) showed that private firm owners tend to follow the pecking order theory regardless of whether the firm is debt constrained or not. Further, Shyam-Sunder and Myers (1999) empirically showed that the pecking order theory has greater illustrative power than the trade-off theory does in explaining a firm's capital structure. Frank and Goyal (2003) argued that the theory fails when tested for small firms, where information asymmetry is a significant problem. Despite these mixed results, the related studies are in consensus that firms prefer not to raise capital through equity under conditions of high information asymmetry because the costs incurred are the highest. Further, they may resort to using equity only during periods of financial distress (Natalia 2011). However, currently, many publicly listed firms raise equity not only during economic disruption periods, but also during stable economic periods, thereby rendering its advertised effectiveness during financial distress periods questionable (Greenstone, Mas & Nguyen 2014).

The third, the adverse selection theory that Myers and Majluf (1984) proposed, focuses specifically on equity issuance. They posit that in a world with asymmetric information, managers take advantage of periods of overvaluation to issue equity based on the superior information they possess about the value of their firm. This theory is commonly used to explain investor reactions when firms issue SEOs. Although rational investors are aware of the stock overvaluation, investors still wait for confirmation via the SEO announcement, which is then followed by a negative stock price reaction (Murgulov 2006). As the information moves through the market, the issuance of SEOs can cause long-term underperformance for up to five years (Allen & Soucik 2008; Loughran & Ritter 1995; Spiess & Affleck-Graves 1995). These authors argue that this effect occurs because of the increase in the number of shares outstanding, which dilutes the ownership percentage of existing shareholders each time an SEO occurs.

The last, Baker and Wurgler's (2002) market-timing theory asserts that market timing is a firm's most important consideration when deciding to issue debt or equity. The theory suggests that firms can capitalise on an inefficient capital market and information asymmetry by timing a share issue to their benefit. Melia (2018) highlighted that the timing of the equity issue is manifested through three main channels. First, a firm issues equity in periods when its share price is overvalued relative to the book value, given the positive shareholder sentiment in such periods that makes it easier to raise equity (Asquith & Mullins 1986; Hovakimian, Opler & Titman 2001; Jung, Kim & Stulz 1996; Korajczyk, Lucas & McDonald 1991; Marsh 1982; Taggart 1977). Second, if firms are aware that their share price is overvalued, they are more likely to experience term negative abnormal returns after the equity issuance as the price slowly retreats closer to its book value to reflect the extent of ownership dilution experienced by existing shareholders. As a result, firms are more likely to issue SEOs when the share price is overvalued (Brav & Gompers 1997; Jegadeesh 2000; Loughran & Ritter 1995; Ritter 1991; Speiss & Affleck-Graves 1995; Stigler 1964). Last, firms commonly issue equity when investors are expecting positive earnings forecasts, making it appear as a high-yield, credible investment from the shareholders' perspective (Denis & Sarin 2001; Loughran & Ritter 1997; Rajan & Servaes 1997; Teoh, Welch & Wong 1988). Most current research on capital structure continues to reference Baker and Wurgler's (2002) market-timing theory as the most appropriate for it explains market behaviour with the highest degree of accuracy (Chen, YW, Chou & Lin 2019.

In summary, the consensus reached by recently developed theories is that firms use internal funding, debt finance or equity finance to fund their operations. Since the present thesis focuses on equity raising in the form of SEOs, the related capital structure theories relevant to this thesis are the adverse selection model and the market-timing theory. Thus, these are the theoretical foundations of this thesis that aims to ascertain and understand the determinants of abnormal SEO return volatility in financial markets.

2.3 Overview of the Australian Financial Market

In addition to issuing SEOs in the three specific periods of economic disruption considered in this study, which account for a large proportion of the total SEO issuances included, notably, firms issued SEOs across the entire study period in order to support their ongoing growth. As Figure 2.1 shows, the use of SEOs by ASX-listed firms has significantly increased every year over the past 10–12 years, rather than only during periods of economic disruption. Thus, to capture these changes, this thesis explores the abnormal SEO volatility and its determinants across the entire sample period as well as during the three periods of economic disruption considered (discussed in Section 2.3.1).

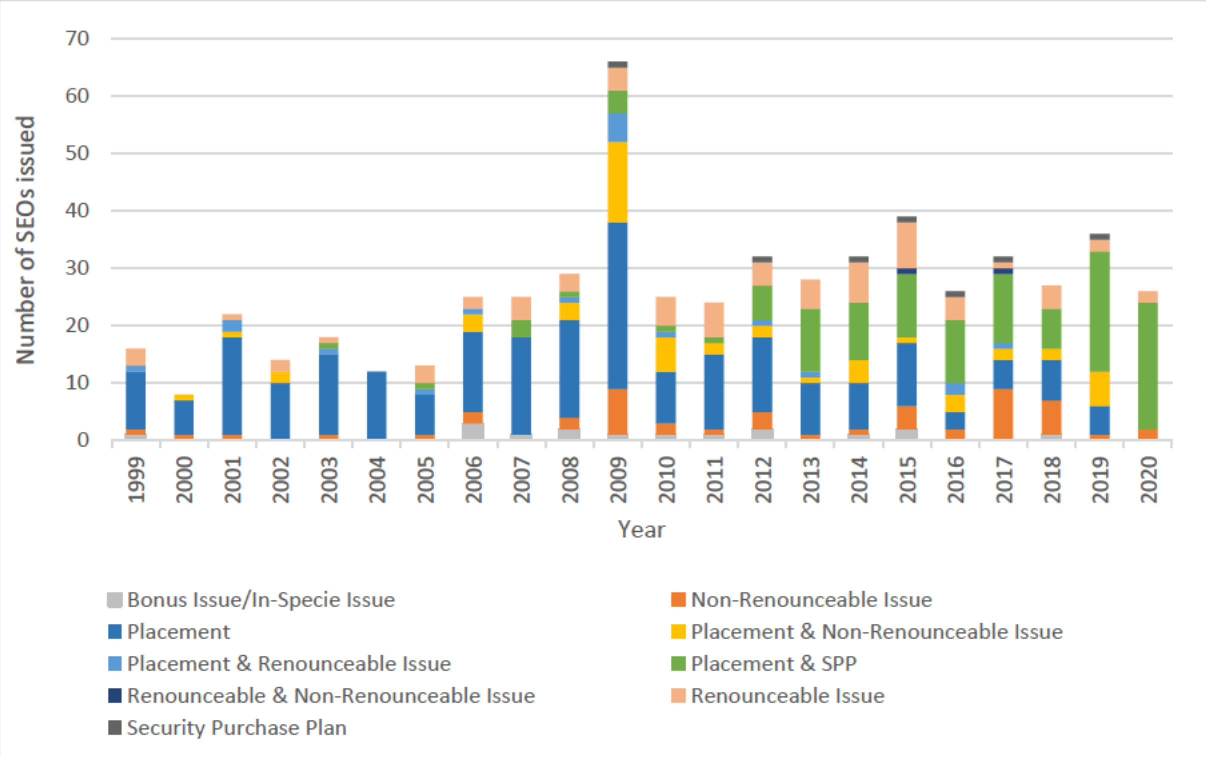

Figure 2.1: Trends in Australian SEO Issuances in 1998–2020 (by SEO Type)

2.3.1 Entire Sample Period

Australia has experienced an unexpected stretch of prolonged economic growth (since the technical and prolonged recession it experienced in 1991), which has contributed to the growth of many firms and, by extension, the sectors in which they operate. During this time, the

Australian economy has certainly experienced many turbulent periods, such as in the early 2000s owing to the dot-com bubble, in 2008 during the GFC and, most recently, during the ongoing COVID-19 pandemic that commenced in 2020, which instigated high levels of stock return volatility. However, despite these economic disruptions, firms have experienced exponential levels of growth (and consequently, volatility), which they supported via SEO issuances. The major drivers of this increased growth and volatility were the country' population growth, ageing population, export growth and growing service economy (Parliament of Australia 2018). The growth in these areas has led to significant increases in Australia's gross domestic product owing to the improved profitability of firms. Most recently, the explosive growth of the Information Technology sector (most notably during the COVID-19 pandemic) has facilitated the rise of the Australian gig economy[2] (FairWork 2021). Over the past 12 years, an uncanny similarity can be identified between the exponential growth of many sectors in Australia and the increase in SEO issuances. This aspect highlights that the growth of ASX-listed firms has been made possible, in part, by the availability of funding through equity capital (i.e. SEOs). Firms have also heavily relied on SEOs to raise capital owing to the influx of investors into the stock market (particularly during the current low interest rate environment), which has caused a large amount of money to flow into this market resulting in the observed increase in stock return volatility (ASIC 2020a). Therefore, exploring the extent of SEO-induced volatility during the entire sample period is of equal importance, to ensure that firms can continue to regularly raise capital during healthy stages of the economic cycle while also protecting investors from experiencing abnormal levels of return volatility.

[2] A gig economy refers to a labour market that consists primarily of short-term contracts or self-employed freelance jobs as opposed to a permanent role. These types of employment become very prevalent during economic downturns.

2.3.2 Early 2000s' Dot-com Bubble

As the internet was being rolled out in the mid-1990s, many firms, particularly those in the US, desired to become part of this new era of technology. A speculative bubble arose from firms simply adding 'dot-com' to their name, causing a frenzy of investors seeking to make quick returns on their investments (Reserve Bank of Australia 2003). The fact that the market cycle appeared to be stable up until the late 1990s caused investors to believe that the market was not overvalued and that, consequently, there was still room for growth to make further capital gains. This belief benefited firms that wanted to join the 'dot-com' frenzy because it resulted in an abundance of investors available to fund their operations through an IPO (Reserve Bank of Australia 2003). This environment led to the parabolic growth of the stock market in November 1999, particularly the technology-heavy NASDAQ Index in the US, which experienced a 70% growth rate from November 1999 to March 2000 (Reserve Bank of Australia 2003). However, with no warning, the stock market started to collapse at the end of March 2000, losing about 70% within a year and bottoming out by September 2002, losing a total of approximately 83% from its peak.[3] Although the Australian market was not as severely affected as the US market, it still experienced an extended period of uncertainty that fuelled excessive levels of volatility due to large daily market swings. During the entire crash period of about 2 years, firms became heavily reliant on SEOs to help repair their balance sheets and survive.

2.3.3 Global Financial Crisis

The GFC stemmed from the US subprime mortgage market and the mortgage-backed securities (collateralised debt obligations) associated with these mortgages. The breakdown of the financial system commenced in 2005–2006, a period in which investment firms (e.g. Bear

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[3] The percentage loss in the NASDAQ Index and the time it took for the market to bottom out was determined based on charting tools obtained from TradingView. Direct link: https://www.tradingview.com/chart/hUVxaLe3/?symbol=FRED%3ANASDAQ100

Stearns and Lehman Brothers) incentivised commercial banks to approve subprime mortgages in exchange for large commissions and bonuses. Because many individuals and their families who were not creditworthy were being approved for a loan, a housing bubble started to form. By October 2007, the market overheated and started to collapse because of the skyrocketing mortgage default rates, and the mortgage-backed securities began to fall in value. This issue severely affected many businesses in the US Financials sector, and several filed for bankruptcy. The domino effect dragged down international markets and caused the market capitalisation of all major indices (e.g. US (S&P 500, NASDAQ), UK (FTSE 100, Russell 2000) India (NIFTY 50), and Germany (DAX)) to fall. This decline compounded into severe levels of market volatility that caused a contagion effect on the ASX 200 Index, which fell by approximately 55% by March 2009 from its peak in October 2007. However, the country was strategically placed in that the GFC effects were not as harsh in Australia as in the US and many European countries owing to the Australian Government's financial support to the affected financial institutions and individuals. This support involved guaranteeing the value of all deposits held by Australian banks (up to AUD250,000 per person) because they were 'too large to fail' (ASX 2010). Furthermore, the government also provided stimulus packages to households in October 2008 and again in February 2009 to stimulate economic growth (Li, SM & Spencer, 2016). Although firms could have raised equity, the significant levels of market volatility and the consequent weak market sentiment made it difficult to raise new equity via SEOs. Thus, the only way that firms could entice investors was by providing significantly larger discounts and seeking underwriting support on their SEOs (ASX 2010). Despite these difficulties, many ASX-listed firms were able to obtain enough equity capital via SEOs in order to replenish their balance sheets and emerge relatively unscathed from the GFC.

2.3.4 2020 COVID-19 pandemic

The COVID-19 pandemic had a rather interesting impact on stock market volatility. The 2020 calendar year had a strong start, given the booming Health Care and Information Technology sectors, and caught the tailwind from 2019 (Alam, Wei & Wahid 2020). Furthermore, the ASX 200 Index reached a record high in February 2020. This record streak was halted when the World Health Organization officially upgraded the '2019 novel coronavirus disease', that is, COVID-19, to a global pandemic in March 2020, causing the ASX to plummet approximately 40% in the space of a month.[4] Interestingly, investors saw this fall as a buying opportunity and snapped up as many shares as they could, causing Australian and international markets to experience a V-shape recovery and recoup most of the losses within just a year (Mahata et al. 2021). However, many businesses that were directly affected by lockdowns experienced significant levels of financial stress, which resulted in widespread unemployment that reached 7.4% in July 2020 (Australian Bureau of Statistics 2020). The hardest-hit firms were those in the tourism industry within the Consumer Discretionary sector and those in the Real Estate sector because firms did not renew commercial property leases for their employees had started working from home. In contrast, the major beneficiaries of the COVID-19 pandemic were the Consumer Staples, the Consumer Discretionary (retail shopping industry only), the Health Care and the Information Technology sectors (Alam, Wei & Wahid 2020). As the profits of firms in these sectors grew during the pandemic, so did the number of eager retail investors. In addition, firms whose share price had been negatively affected by the pandemic were able to raise equity relatively effortlessly. This is because the pre-pandemic investors of these firms understood that these shares were highly undervalued and were therefore more than willing to participate in SEOs to take advantage of the discounted share price.

[4] The percentage loss in the ASX 200 Index and the time taken for the market to bottom out was determined by using charting tools obtained from TradingView. Direct link: https://www.tradingview.com/chart/hUVxaLe3/?symbol=ASX%3AXJO

2.4 Seasoned Equity Offering Trends in Australia

After the US, Australian firms are among the most prolific issuers of SEOs in the world, and they have contributed 21.6% of total global equity issues as of 2010 (McLean 2011). As of 2020, the ASX is the most active exchange globally in terms of number of SEOs issued and second most active with respect to the value of equity capital raised (ASX 2020b). Primarily, the introduction of the dividend imputation system in July 1987 kickstarted this trend. This system allows Australian firms that have paid tax on their earnings to pass on these benefits to shareholders in the form of franking (tax) credits to ensure that investors do not incur double taxation on their dividends from shares (Melia 2018). After the implementation of this system, Australian firms found it attractive to raise capital using equity and thereby decrease their debt-to-equity ratios (Balachandran, Faff & Theobald 2009; Fan, Titman & Twite 2012). Pattenden and Twite (2008) also showed that this system led to an increase in dividend payout ratios. This increase ultimately enticed individuals to invest in firms that pay dividends for it allowed them to generate passive income without incurring any tax labilities. Given these incentives, SEO participation rates have increased over time and have remained consistently high (see Figure 2.1). From the perspective of the adverse selection theory and market timing theory, Australian firms can also benefit from issuing SEOs during periods of overvaluation, where the stock price trades above its book value. Signalling a period of positive market sentiment, firms can take advantage of issuing shares at a smaller discount. The smaller discount allows the firm to issue shares at a higher price, thereby reducing the number of shares they need to issue. This helps to reduce the dilutive impact of SEO and thereby minimize the negative stock price reaction after the SEO announcement (Murgulov 2006). Australia is also one of the few countries that provides the freedom for ASX listed firms to issue 'combined SEOs', allowing both institutional and retail shareholder to participate in separate share allocations. The separation prevents institutional shareholders from buying up all the available shares, which provides retail shareholders an equal opportunity to participate in the SEO (Dennis & Strickland 2002; Gabaix et al. 2006; Sias 1996, Xu, Y & Malkiel 2003).

Data from the Morningstar DatAnalysis database was collected to identify trends across the nine types of SEOs issued in Australia: bonus issue, non-renounceable rights issue, renounceable rights issue, private placement, placement & non-renounceable rights issue, placement & renounceable rights issue, placement & security purchase plan (SPP), renounceable & non-renounceable rights issue, and standalone SPPs. The analysis spans the period 1998–2020 to cover three distinct types of economic disruptions, namely, the dot-com boom in the early 2000s, the 2008 GFC and the 2020 COVID-19 pandemic. Figure 2.1 summarises the trends in SEOs issued under each type during the study period. The first observation is that, by far, private placements have been the most preferred SEO type adopted by Australian firms. This is likely because it is the fastest (within 3–4 business days) and cheapest SEO type to administer (Hamilton Locke, 2020). However, since 2012, firms have slowly transitioned away from these standalone private placements towards the combined placement & SPP,[5] and this SEO type has been the most prevalent each year from 2012 onwards. The increased use of the placement & SPP over time shows that firms have been actively trying to include both retail and institutional investors in the equity-raising process. Second, SEO issuances were the highest in 2009, fuelled by firms raising large amounts of capital to counter the harmful financial effects of the GFC. Third, since 1998, overall, the SEOs issued within the Australian capital market have increased, indicating that firms have become increasingly reliant on SEOs as the preferred form of capital raising. This finding suggests that Australian firms consistently took advantage of equity raising whenever they required capital (during the entire sample period as well as during economic disruption periods). The fact that

[5] The difference between a private placement and a placement & SPP is that the former is restricted to institutional investors, whereas the latter allows institutional and retail investors to both participate in the equity-raising process. This is discussed in detail in section 2.5 of this chapter.

many ASX 200 listed firms increased their reliance on SEOs during periods of economic growth as well as economic disruptions highlights that they are closely aligned to the adverse selection theory and the market-timing theory.

Figure 2.2 shows the total number of SEO issuances within each Australian sector across the study period. The SEO market has been dominated by the Materials sector. This is because this sector has received extensive private funding to exploit the high returns of the early to mid-2000s Australian resources investment boom, making it a low-risk investment (Arsov, Shanahan & Williams 2013; ASX 2010). The high return coupled with the low risk has made this sector very attractive to investors, who have therefore shown increased willingness to participate in SEOs. Following this sector was the Real Estate sector in which equity raising was primarily concentrated around the dot-com bubble in the early 2000s and the 2008 GFC. During these periods, the Real Estate sector experienced substantial losses from the deterioration in the value of residential and commercial properties and thus required substantial amounts of equity capital to survive. Following closely behind were the Financials, the Consumer Discretionary, the Industrials and the Health Care sectors, which raised equity relatively consistently each year (as shown in Figure 2.3). Although the remaining sectors (Consumer Staples, Energy, Information Technology, Communication Services and Utilities) issued SEOs, these did not undertake a high volume of SEOs during the sample period. A likely reason is that they have either operated on a low degree of external funds or utilised another form of capital raising, such as debt issuance (i.e. corporate bonds), debt/equity hybrids (i.e. convertible notes) or borrowings from lending institutions (Fang, Kosev & Wakeling 2015).

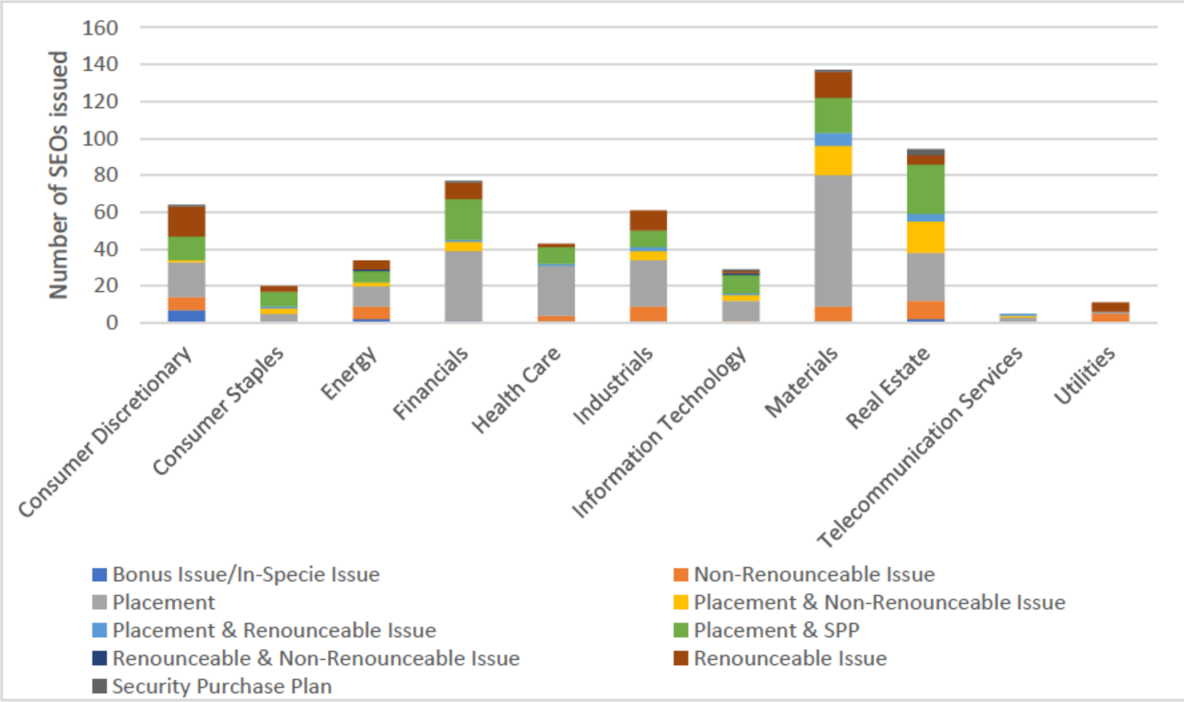

Figure 2.2: Total Equity Issuances Classified by SEO Type in Each Sector

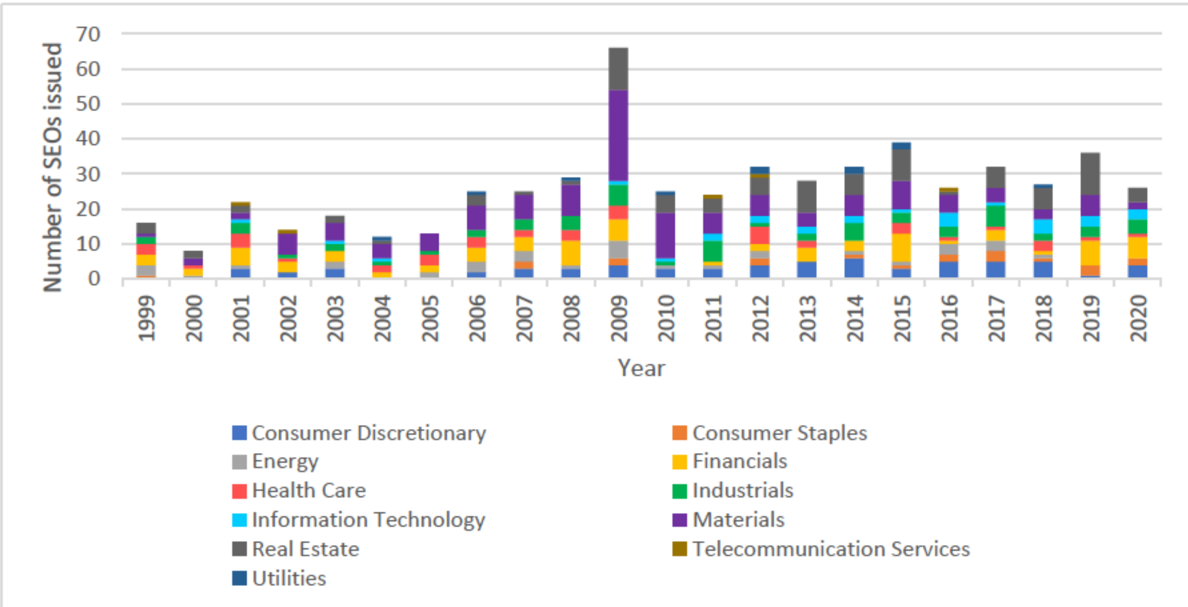

Figure 2.3: Trends in Australian SEO issuances 1999–2020 (by Sector)

2.5 Types of SEOs Issued in Australian Market

Publicly listed firms worldwide use many types of SEOs. Although the types available across each country vary slightly, many SEO types do overlap from country to country. In this research, the primary focus is on the SEOs issued by ASX-listed firms, which are classified as (i) restricted, (ii) standalone or (iii) combined SEOs[6] and overlap with those issued internationally. The next section discusses each SEO type issued in Australia during 1998–2020, including the benefits and drawbacks[7] of each.[8]

2.5.1 Private Placement

A private placement refers to the issuance of securities to an exclusive group of existing institutional shareholders who hold large blocks of shares in the firm (Melia 2018). Examples of institutional investors include investment banks, superannuation funds, hedge funds and high-net-worth individuals. The benefits of private placements include:

1. The turnaround time (i.e. execution and settlement) is very short (between 3 and 4 business days), allowing firms to raise capital very quickly, which is crucial during economic disruptions.
2. They carry the lowest risk from the perspective of the issuing firm because it is raising capital from well-known institutions who have a credible history and a larger amount of capital available on demand (ASIC 2016).
3. The issuance and underwriting costs are the lowest among all SEO types. This is a large advantage for firms because such costs are the largest expense in an SEO.
4. The spread between the discount price and the market price is usually smaller than in the other SEO types. This is because the firm allows institutions to purchase larger blocks of shares at a time. Thus, to decrease the dilutive impact on existing shareholders, the SEO discount is usually smaller.

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[6] A combined SEO is one that consists of an institutional and a retail component.
[7] Hamilton Locke (a Sydney-based law firm) provided a succinct summary of SEOs used in the Australian landscape and their features at https://www hamiltonlocke.com.au/sites/default/files/2020-10/Raising%20Capital%202020.pdf
[8] The timetable for all SEOs is detailed on the ASX website at https://www.asx.com.au/documents/rules/Appendix_07A.pdf.

5. They can be issued in combination with renounceable or non-renounceable rights issues or with SPPs.
6. The firm need not prepare and supply a prospectus to institutional investors.
7. Firms are limited to issuing up to 15% of the existing number of shares outstanding within a 12-month period to avoid over-dilution. Over-dilution occurs when a firm issues a large number of shares in a short period, which causes a significant drop in the share price after the SEO announcement.

The drawbacks of private placements include:

1. They have the potential to cause shareholder dilution to the largest extent in comparison with the other SEO types. This is caused by the fact that only institutional investors can partake in the SEO, resulting in retail investors being excluded and losing a larger percentage of ownership in the firm.
2. A larger percentage of ownership allocation to institutional investors dilutes the voting power of existing shareholders.
3. The drastic increase in the supply of shares outstanding can negatively affect the share price. After the private placement announcement, the price may not only move towards the discount price but may even fall below the offer price, depending on the reactions of the retail investor who were excluded from the SEO.
4. Retail investors are informed about the private placement only after it has already occurred via a ‘cleansing notice’.
5. The 15% limit is regularly increased, depending on the circumstances. For example, if the firm is issuing shares to an institution that is not included on the ASX 300 Index and has a market capitalisation less than that prescribed by the ASX (approximately AUD300 billion), the SEO-issuing firm can raise an additional 10% from the ‘eligible’ institution. Other circumstances include the temporary easing of limits during economic

disruptions, from 15% to 25%. Although these limit increases are beneficial for the firm, they affect existing shareholders negatively.

2.5.2 Rights Issue

A rights issue refers to the process of providing existing shareholders the opportunity, but not the obligation, to purchase additional shares. These shares are offered at a firm-specified discounted price on a pro-rata basis. The firm also decides the pro-rata ratio, depending on the number of additional shares it is willing to issue with consideration of the consequent dilution effects on existing shareholders.

The two main types of rights issues are renounceable and non-renounceable rights issues. The former allows existing shareholders of the firm to sell their right or entitlement to a third party who is not required to be an existing shareholder. This provides some flexibility to the existing shareholders and allows them to gain some value for their rights if they are unwilling or unable to participate in the renounceable rights issue. In contrast, a non-renounceable rights issue does not allow shareholders to transfer their right or entitlement to a third party. If they do not wish to exercise their right to purchase additional shares, they are subject to the negative effects of share dilution. A firm usually opts for a non-renounceable rights issue if it believes that the market has a low degree of liquidity and that thus it is unlikely that there will be demand for the rights in the open market. In contrast, firms that have a higher degree of liquidity may find renounceable rights issues to be a more preferable option.

Other types of rights issues include accelerated rights issues,[9] which are the same as a rights issue; however, the proceeds from institutions are received in a shorter timeframe (2–3 days).

[9]Examples of accelerated rights issues are ANREO (accelerated non-renounceable entitlement offer), AERO (accelerated renounceable entitlement offer), SAREO (simultaneous accelerated renounceable entitlement offer) and PAITREO (accelerated renounceable entitlement offer with retail rights trading).

Accelerated rights issues are included in this study and have been grouped with other rights issues according to whether these were renounceable or non-renounceable in nature.

The benefits of rights issues are:

1. It provides the opportunity for existing institutional and retail shareholders to engage in the SEO. In addition to promoting the fair treatment of institutional as well as retail investors, it provides two other main benefits to each investor: It allows them to purchase additional shares at a discounted price, and it helps to buffer against the negative effects of share dilution (ASIC 2016).
2. The requirements of rights issues have some exemptions under the *Corporations Act 2001*. The ASIC has further applied these exemptions to accelerated rights issues for increasing the appeal to ASX-listed firms.
3. It can offer renounceability to investors, which allows them to trade their rights in the open market if they choose to not take up the rights offer.
4. The disclosure requirements are substantial, which means that investors receive extensive information about the SEO well in advance of it occurring.
5. The SEO discount (the difference between the offer price and the market price on the announcement date) is usually larger than that of the other SEO types, which increases the chances of success. This fact also provides investors a greater incentive to purchase additional shares at a lower price.
6. No limit is specified on the amount of capital that the firm is allowed to raise, allowing smaller firms to take advantage of greater capital requirements for growth.

The drawbacks of rights issues are:

1. The cost of preparing the prospectus (legal, accounting and underwriting costs) and other disclosure requirements is higher than that for a private placement in which disclosure requirements are limited.
2. The processing time (up to 23 business days based on Appendix 7A of the ASX Listing Rules) before the shares are issued to shareholders is lengthy.
3. It is available only to existing shareholders, which limits the amount of capital that the firm can raise.
4. It is offered on a pro-rata basis, which means that existing shareholders can only purchase a set number of shares, depending on the number they were holding at the time of the SEO announcement. For example, a 1-for-10 issue means that a shareholder can purchase an additional share at the specified discounted price for every 10 shares they hold. The reason that firms offer shares on a pro-rata basis is to ensure that they control for the effects of share dilution. However, the downside to this practice is that it limits the amount of capital that firms can raise.
5. A large discount (compared with private placements) can lead to larger post-announcement stock price falls. Rights issues tend to have larger discounts than private placements because they are also offered to retail investors, who require a larger incentive than institutions do to participate in SEOs. However, as the market-timing theory suggests, a larger discount signals that the firm believes its share price is overvalued, given that it is willing to issue additional shares at lower valuations. Thus, the share price typically falls by a similar percentage that is dictated by the discount. For example, if shares are offered at a 10% discount, the share price will usually fall by approximately 10% shortly after the SEO announcement.
6. The slower processing time and increased disclosure requirements make it a less attractive SEO than private placements during economic disruption periods.

7. Firms can offer non-renounceability on the rights issues and therefore prevent investors from selling their rights in the open market, which makes them experience stock dilution to a larger extent if they do not participate in the SEO than when they do participate.

2.5.3 Share Purchase Plan

The SPP involves an offer of shares to existing shareholders up to a specified dollar value. Although an SPP can be offered to all shareholders equally, it is not commonly issued as a standalone SEO, but in conjunction with a private placement. SPPs are similar to rights issues in that they are offered to existing shareholders but differ in that they are not offered on a pro-rata basis (ASIC 2016).

The benefits of SPPs are:

1. They allow all shareholders to maximise the number of shares they would like to purchase without being restricted by the number of their existing shares. This provides a greater compensation for retail shareholders over institutional shareholders.
2. SPPs allow firms to raise up to AUD15,000 over a 12-month period from existing shareholders without needing to provide disclosure documents. However, they are still required to issue a 'cleansing notice'.
3. SPPs can be kept open for 3–6 weeks, depending on the discretion of the board of directors.
4. SPPs have lower transaction costs for, usually, they are not underwritten, and therefore, no underwriting fees are charged. The only costs involved would be legal costs and disclosure documentation (i.e. a brief SPP booklet) preparation costs.
5. An SPP can be issued in conjunction with a private placement to allow retail shareholders to participate in private placements.

6. Investors do not incur brokerage costs to obtain additional shares.

The drawbacks of SPPs are:

1. Any existing shareholder who does not subscribe to shares in the SPP will ultimately suffer the effect of share dilution. The extent of dilution is based on the number of shares bought by the other existing shareholders.
2. There is a longer period between SPP execution and the settlement date.

2.5.4 Bonus Issues

A bonus issue refers to the shares of a firm that are issued to existing shareholders at no cost (Morningstar 2021). As in the case of rights issues, these shares are usually issued on a pro-rata basis to prevent shareholder over-dilution. Firms choose to undertake a bonus issue for numerous reasons. One is that the firm may issue bonus shares in lieu of increasing its dividend yield (Basra & Singla 2019). When investors expect an increasing dividend yield, but the firm has less cash to pay dividends, it can issue bonus shares. After the bonus issue, shareholders can sell the bonus shares (after the firm-specified period) to provide them the same liquidity as that of a dividend payment. The benefit to the firm of issuing bonus shares is that it increases the number of shares outstanding, which increases its market capitalisation, and therefore, the firm appears to be larger in size (Ball, Brown & Finn 1977). Larger firm sizes are usually considered more attractive to investors because these firms are assumed to be low-risk investments. The major drawback of a bonus issue is that it results in the largest degree of share price dilution because the shares are offered for free to existing shareholders, and thus, the discount is effectively 100%.

The core objective of this thesis is to provide a framework that allows firms to choose an SEO type to help boost their cash when needed while also protecting their investors from abnormal return volatility. Since bonus issues do not actually raise cash for the business, they do not serve to address the objectives of this thesis and therefore are not studied extensively. However, for the purpose of completeness, the abnormal return volatility is measured around bonus issues in Phase 1.

2.5.5 Dividend Reinvestment Plan

A dividend reinvestment plan (DRP) is a structure that allows shareholders to reinvest their dividends into the business and obtain additional shares. As the name suggests, only firms that issue dividends to shareholders can take advantage of this structure (ASX 2010). The benefits of DRPs are that they allow shareholders to obtain additional shares at a discounted price. DRPs also have a high degree of flexibility, whereby investors can suspend or resume the reinvestment plan at their own discretion. One drawback is that the capital-raising prospects are capped at the amount distributed as dividends. Another drawback is the inflexible timing, which means that firms can only expect to obtain additional capital during dividend distribution times, rather than in times of need. Moreover, the amount of capital that is raised is limited to the size of the dividend payment as well as the number of shareholders who participate in the DRP.

For the same reason that it excludes bonus issues, this thesis excludes DRPs since it only focuses on SEOs that provide new cash for the business. Another reason is that this thesis aims to identify the SEOs that firms can choose during economic disruption periods. During these times, firms usually do not issue a dividend payment to their investors, and thus, will not find it useful to consider DRPs during such periods of economic uncertainty.

2.6 Regulators' Role in Equity Raising

2.6.1 Historical Role of Regulators in SEOs

Since 1987, equity issuances have been prevalent in the Australian market. Over time, regulatory bodies have strived to facilitate fairness in the market to ensure that firms can raise equity capital whilst also protecting the interests of investors in the process. Since rights issues and private placements (and the combination of both) are the most widely used, most regulatory improvements have been made to these SEO types.

Because rights issues are offered on a pro-rata basis, the fixed costs are higher than for private placements owing to the management fees payable and the cost of preparing a prospectus document. However, in June 2007, the ASIC amended the *Corporations Act 2001* to allow a 'low doc' prospectus, which is a simplified version of a full prospectus, if the firm also submits a cleansing notice document to the ASX (ASIC 2016). These measures helped firms to save time and money and motivated them to prefer rights issues instead of private placements.

2.6.2 Temporary Regulatory Easing During Economic Disruptions

During the periods of economic disruption, the ASX and ASIC introduced measures to support the equity-capital-raising process for ASX-listed firms (ASX 2020a). The requirements for equity raising were relaxed to incentivise the use of equity to raise capital rather than debt (for which interest is paid, which could further affect a firm's profitability negatively). Some examples of requirements that were relaxed to facilitate equity raising during economic disruptions include:

- Allowing firms that do not meet all the usual capital requirements needed, to issue 'low doc' offers for rights issues, standalone private placements and standalone SPPs. This was done to allow firms to speed up the capital-raising process and keep costs low.
- Allowing firms to undertake two back-to-back trading halts, if needed, totalling four trading days. If the firm was unable to complete the capital-raising process within this time, it could voluntarily suspend trading for up to 10 days.
- Waiving the one-for-one cap on non-renounceable rights issues, thereby allowing the firm to choose its own pro-rata ratio that it believed was fair and reasonable.

- Increasing the private placement limit temporarily, from 15% of the number of shares outstanding to 25%, with a follow-up SPP for retail investors. For example, assume that a firm had 1,000,000 shares outstanding and intended to issue additional equity via a private placement. Instead of only being able to issue a maximum of 150,000 additional shares, they would be able to issue 250,000 new shares to existing institutional shareholders.
- Temporarily waiving the restriction specified under listing rule 7.1A on the maximum SEO discount percentage (25% of the volume weighted average price over the 15 trading days before the SEO announcement) and the number of shares that can be issued under an SPP (ASX 2021c).

Interestingly, although these measures have helped firms continue their operations during turbulent economic periods, little consideration has been given to the likely effects on existing shareholders (particularly retail shareholders). The easing of many regulations results in existing shareholders experiencing high levels of volatility. However, to date, Australian regulators have not addressed this fundamental issue, as clearly shown through the recent five priorities established in the ASIC's interim corporate plan for 2020–2021 (ASIC 2020d). Unfortunately, these five priorities do not directly address the issue of protecting investors during periods of high market volatility and intensive capital raising. This is the area of concern that this thesis aims to highlight to regulators.

2.7 Summary

Chapter 2 provided an overview of the Australian SEO market as well as of the theories of capital structure that are relevant to this thesis. Specifically, this chapter highlighted the adverse selection model and the market-timing theory as the relevant theories. This chapter also provided an explanation of the various economic periods of interest selected for consideration in this thesis. In addition, the various types of SEOs used by ASX-listed firms were discussed, and justification was provided for the decision to include or exclude specific SEO types from this study. Last, the role of regulators in SEO issuances was discussed, with a focus on the easing of regulations to help firms raise capital during periods of economic disruptions. The next chapter reviews the existing literature on SEOs upon which the hypotheses of this thesis are developed. Specifically, the chapter provides a critique of the literature on the determinants that may instigate abnormal return volatility across each SEO type and sector.

Chapter 3: Literature Review and Hypothesis Development

3.1 Introduction

Chapter 3 provides a review of the academic literature about the measurements of abnormal return volatility and its potential determinants. The chapter is divided into three main sections. First, section 3.2 provides an overview of the reaction of market participants to SEO announcements. Second, section 3.3 explores the literature regarding the various proxies used to capture abnormal return volatility and assesses their accuracy, which forms the basis of Hypothesis 1 and 2. Third, section 3.4 explores the literature on the potential determinants that can be used to explain the observed changes in the abnormal return volatility during SEOs. The discussion on these determinants is used to formulate Hypothesis 3 to 12. The last section of this chapter summarises the contributions of the thesis to the SEO literature.

3.2 Overview of Market Reactions to SEOs

Myers and Majluf's (1984) seminal study proposed the adverse selection model, which posited that superior information is held by the firm's managers regarding the underlying performance of the business, which indicates a high degree of information asymmetry. Interpreting this asymmetry as a negative signal, the stock price falls upon the release of the SEO announcement, driven by the reduction in the valuation of the firm by shareholders. Numerous studies have confirmed that negative stock returns are the reaction to SEO announcements (Asquith & Mullins 1986; Lucas & McDonald 1990; Masulis & Korwar 1986; Schipper & Smith 1986; Spiess & Affleck-Graves 1995).

More recent studies have focused on researching not only market reactions to SEOs, but also the degree to which the stock returns fluctuate around the announcement (i.e. abnormal returns). Several studies have observed a pre-announcement increase in abnormal returns, followed by a drop in abnormal returns following the announcement, which provides support to Myers and Majluf's (1984) adverse selection model (Carlson, Fisher & Giammarino 2006; Kim & Purnanandam 2006; Liu, J et al. 2016). This negative reaction has led researchers to explore ideal windows of opportunity for firms to time the market and thereby maximise the amount of capital raised (Bayless & Chaplinsky 1996).

However, conflicting evidence exists on the ideal time when the SEO should be issued, owing to differences in assessment. Some studies have argued that firms should issue SEOs during high information asymmetry periods, which is typically observed during high economic growth periods (Korajczyk, Lucas & McDonald 1991; Krasker 1986; Lucas & McDonald 1990). Conversely, others have contended that periods of low information asymmetry are ideal, which is more common during more stable economic periods (Bayless & Chaplinsky 1996; Choe, Masulis & Nanda 1993).

Although both arguments are valid, the window of opportunity to issue SEOs largely depends on the anticipated use of the funds. If firms plan to use the funds for business growth, it is ideal to capitalise on SEO issuance during high information asymmetry periods because there will be greater demand for a firm's shares if the business is expected to expand in the future (Myers & Majluf 1984). This expectation is also likely to incentivise investors into paying a premium for the shares (Huang, Uchida & Zha 2016). In contrast, if a firm needs the funds for balance-sheet replenishment, it is ideal to issue SEOs during low information asymmetry periods (Korajczyk, Lucas & McDonald 1991).

Moreover, during low information asymmetry periods, market sentiment is also low, which means that firms will have to offer shares at a discount to increase investor participation rates and the probability of raising the desired amount of capital. Both periods are considered 'hot' issue periods and are the ideal windows of opportunity to maximise the amount of capital raised (Bayless & Chaplinsky 1996). The action of firms timing SEO issuances to suit their personal preferences are likely to elicit abnormal levels of stock return volatility. Such volatility can negatively impact investor confidence and may hinder the firm's capability to raise capital in the future (Chen, YW, Chou & Lin 2019; Chou & Lin 2015).

3.3 Measurements of Abnormal Return Volatility

Walker and Wu (2019) argued that when firms experience financial distress, they gravitate towards equity raising (via SEOs) compared to taking on debt, partly because of the expedited nature of equity raising. Moreover, the capital raised during economic disruptions is considerably larger because regulators tend to increase capacity limits, which does not typically occur when firms issue SEOs during business growth phases which occur during stable economic periods (ASX 2020a). The higher limits increase the degree of shareholder dilution, resulting in a decrease in the stock price (Asquith & Mullins 1986). Nelson (1991) argued that this reaction occurs because investors perceive dilution negatively, which often leads to a larger (and possibly abnormal) effect on volatility than does positive news. Moreover, Black's (1976) leverage effect suggests that when bad news is released during periods of economic disruption, in which confidence is low, the negative reaction is compounded and may perpetuate volatility. Chen, Chollete and Ray (2010) also argued that a firm's financial distress risk (risk of failure to meet financial obligations) is positively related to volatility and that this risk tends to be highest when the economy performed poorly.

Thus, the present research argues that the volatility during SEO announcements is abnormally high when firms are in financial distress, which is typically observed during economic disruptions. The most common way to measure abnormal return volatility is through the AVAR proxy. Initially proposed by Bever (1968) and improved upon by Landsman and Maydew (2002), this proxy captures the changing consensus of the market through measuring the degree of investor reactions to SEO announcements. This is measured through comparing the expected investor reaction to the unexpected reaction, thereby highlighting whether the reaction is 'abnormal' or not. As mentioned previously, the three major economic disruptions included in this research as the periods in which many firms were likely to experience financial distress are the dot-com bubble in the early 2000s, the GFC in 2018 and the COVID-19 pandemic in 2020. Hence, the first hypothesis of this research is that there is also an abnormal increase in return volatility during economic disruptions across the entire Australian market. Specifically, it is postulated that:

> *H_1: SEO announcements elicit higher abnormal return volatility during periods of economic disruption in the aggregate market.*

There are a very limited number of studies which examine the relationship between SEOs and stock return volatility, however they present conflicting results. Ho et al. (2005) examined the volatility around SEOs for stocks listed on the aggregate Taiwanese stock market in 1995–1999. They found that the stock return volatility increased during the SEO announcement period. Bae and Jo (1999) also examined SEOs for NYSE stocks during 1968–1995, with a focus on studying the effect of rights issues on stock return volatility. In contrast, they found that during the SEO announcement period, there was a decrease in stock return volatility. Across the landscape of limited SEO-based research, Liu et al.'s (2016) study is the only one that compared how shareholder reactions vary for multiple SEO types (i.e. rights issues, private placements and open offers). For stocks listed on the Shanghai and Shenzhen stock exchanges in 1991–2010, they showed that open offers and rights issues resulted in negative pre- and post-announcement reactions. However, firms issuing private placements initially experienced a negative pre-announcement reaction followed by a positive reaction after the announcement. Given that there are distinct differences in the behaviour of prices during the announcement period of each SEO type, firms may experience distinct and varying levels of stock return volatility, with some experiencing abnormally higher levels than others.

In this research, it is noted that standalone or restricted SEOs[10] comprise retail and/or institutional investors who compete for discounted shares. In restricted SEOs (i.e. private placements), retail investors are excluded completely, whereas in standalone SEOs (e.g. renounceable or non-renounceable rights issues) retail and institutional investors both compete to secure discounted shares. However, since institutional investors tend to have larger holdings, there is a higher probability that they will absorb (or oversubscribe) the shares issued in the SEO, resulting in the exclusion of retail investors. The probability of such oversubscription is high because institutional investors typically possess private information about the firm who is issuing the SEO, which is used to capitalise on the discounted prices (Chemmanur, He & Hu 2009).

To compound this negative effect, to profit from the SEO discount, institutional investors typically subscribe to SEOs over a short investment horizon. This issue leads to not only the exclusion of retail investors, but they also endure further abnormal negative returns, thereby increasing the probability of experiencing abnormal return volatility (Hao 2014). Consequently, retail investors are more likely to lead to capitulation of their existing shares to reduce volatility exposure to their portfolio. Thus, this research posits that firms that issue

[10] Standalone SEOs involve the participation of both retail and institutional shareholder without priority being given to any one particular shareholder type. These include bonus issues, non-renounceable rights issues, renounceable right issues, SPPs and renounceable & non-renounceable rights issues. A restricted SEO refers to a private placement whereby the firm only offer discounted shares to institutional investors.

standalone or restricted SEOs are more likely to experience abnormally higher levels of stock return volatility around the announcement. Conversely, combined SEOs[11] do not suffer from this disadvantage because the issuing firm provides separate offers to institutional and retail investors. This feature eliminates the competition between these two types of investors and therefore eliminates the chance of the latter from being excluded from the SEO. Accordingly, it is expected that these firms are more likely to experience a lower degree of abnormal return volatility. Thus, the following hypothesis is proposed:

> *H_{2a}: Firms that issue standalone or restricted SEOs experience higher abnormal return volatility than firms that issue combined SEOs.*

Hassan and Malik (2007) argued that measuring volatility across sectors helps investors improve their portfolio allocation decisions. Such decisions are particularly critical in mitigating the risk of overconcentrating investments into one sector. Imbs (2007) reported a positive relationship sectoral volatility and sectoral performance whereby high- (low-) performing sectors are more likely to experience higher (lower) levels of return volatility. Since the Australian market consists of a mix of high- and low-performing sectors which make up the two-speed economy, variations in volatility are also expected across each sector (Deo, Spong & Varua 2017). According to Australia's sectoral returns and growth rates,[12] the high-performing sectors include Health Care, Information Technology and Energy. The moderate-performing sectors include Consumer Discretionary, Consumer Staples, Industrials, Materials and Financials. Last, the low-performing sectors include Communication Services, Utilities

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[11] Combined SEOs are a form of equity raising that also includes institutional as well as retail investors. However, each shareholder type has a *separate* pool of shares allocated by the firm, which removes the chance of being excluded. These SEOs include placement & non-renounceable rights issue, placement & renounceable rights issue, and placement & SPP. An example of a combined SEO which depicts the separate allocations of shares to each shareholder type is AfterPay Ltd. This company issued a placement & SPP: https://www.asx.com.au/asxpdf/20190611/pdf/445r1f2dvzsxrm.pdf

[12] Sourced from the Refinitiv Eikon database. Sector performance is determined using the average return of the index sector during the study period.

and Real Estate. Garton (2008) argued that the performance between high- and low-performing sectors experience high divergence during periods of economic disruptions, indicating higher differences in volatility. Choi et al. (2021) also showed that many higher and moderately performing sectors are interconnected and volatility tends to spillover between these sectors. Specifically, the Finance sector is the main inducer of volatility, which spills over to the Energy, and Information Technology sectors. Moreover, the authors also evidenced an increase in volatility spillover intensity during economic crisis periods, thereby resulting in higher volatility experienced by these higher and moderately performing sectors. Similar volatility spillovers were observed by Laborda and Olmo (2021) in the U.S. sectors, where the Financials, Energy and Healthcare sectors experienced the highest levels of volatility. Similarly, during the 2008 GFC and COVID-19 pandemic, the volatility intensified for the Energy and Technology sectors. These findings indicate that higher and moderately performing sectors tend to be the largest inducers and recipients of volatility across financial markets.

Thus, this thesis postulates that during periods of economic disruption, high- (low-) performing sectors will be more (less) sensitive to SEO announcements, resulting in larger (smaller) abnormal return volatility. This is based on the premise that high- (low-) performing sectors are less (more) defensive to market downturns, resulting in investors exhibiting higher (lower) sensitivity to changes in a firm’s capital structure. However, during the entire sample period, high-performing sectors are expected to display a lower degree of abnormal SEO return volatility. This is because investors show a greater level of optimism towards a firm’s future when they made aware that the intended use of the funds is for business growth and expansion rather than replenishing their balance-sheet. Consequently, investors are less likely to be concerned about short-term volatility due to dilution and therefore less likely to capitulate their existing holdings. Thus, the following hypothesis is proposed:

H_{2b}: Firms in high- and moderate-performing sectors experience a larger degree of abnormal return volatility than those in low-performing sectors.

3.4 Determinants of Abnormal Return Volatility

A thorough examination of the literature, with a focus on those that undertake SEOs, reveals a multitude of factors that affect stock returns when equity is being raised. However, little attention has been given to the determinants of stock return *volatility* during SEO issuances. The only study to have explored and confirmed the existence of stock return volatility during SEOs is that of Hibbert et al. (2020), but they focused on how the heterogeneity of investor beliefs influence stock return volatility during SEOs.

The contribution of this thesis is that it not only examines the presence of *abnormal* return volatility, but also uncovers its determinants and the extent to which they instigate abnormal levels of return volatility across various SEO types and sectors. Since capital raising through SEOs is a vital part of the ongoing growth and survival of every business, it is critical for firms to understand the impact of SEOs on shareholders and to take measurable steps to minimise instances of abnormal return volatility. As illustrated in Figure 3.1, these determinants can be characterised into three distinct groups, SEO-specific, firm-specific and market-wide factors, and are discussed in detail in Sections 3.4.1, 3.4.2 and 3.4.3, respectively.

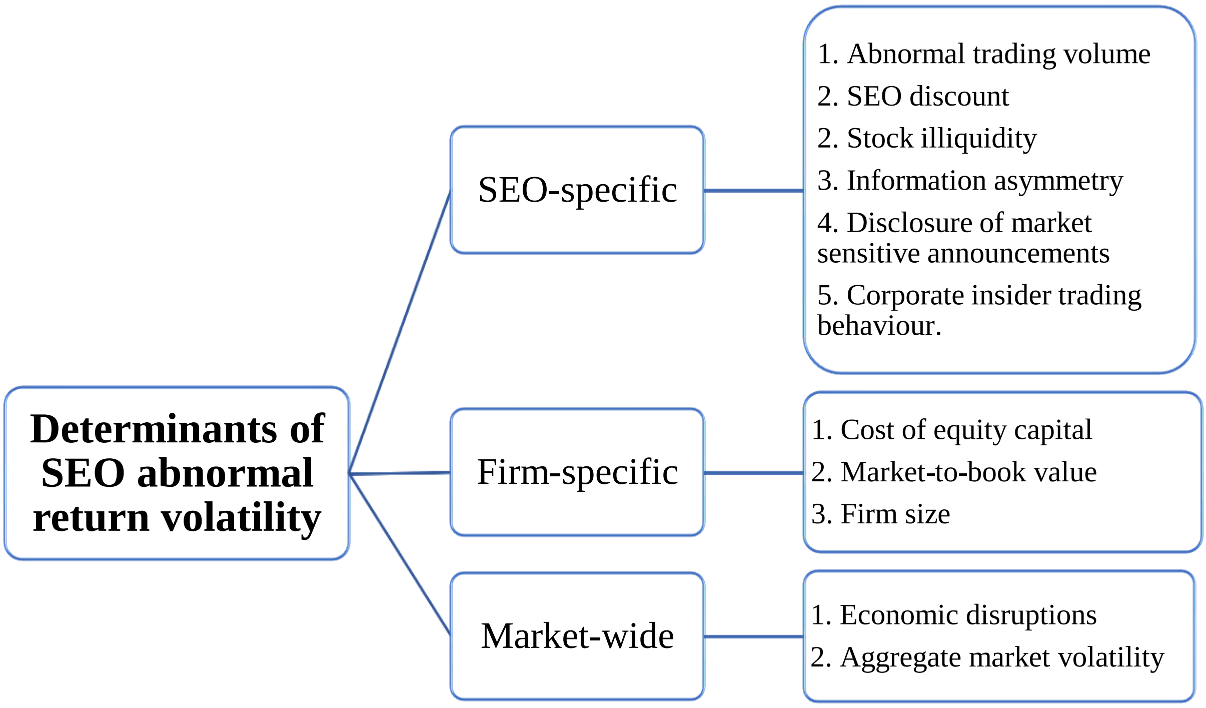


Figure 3.1: Determinants of SEO Abnormal Return Volatility

3.4.1 Issue-specific Factors

3.4.1.1 Abnormal Trading Volume

Morgan (1976) highlighted that an increase in the abnormal trading volume is usually accompanied by an increase in abnormal return volatility. Shahzad et al. (2014) confirmed this relationship by highlighting that abnormal volume and abnormal return volatility have a causal relationship and therefore move together. Moreover, Palkar and Tripathy (2011) and Bae and Jo (1999) revealed that firms' abnormal trading volume substantially increased during SEO announcements. As regards the impact across sectors, abnormal trading volume is expected to instigate higher abnormal return volatility within high-performing and moderate-performing sectors, compared with that in low-performing sectors. This is because the former sectors provide faster growth rates than the latter sector, and thus attract shareholder participation, resulting in higher trading volume during SEOs and therefore higher volatility (He, Jarnecic & Liu 2016). Thus, the following hypotheses are specified:

H_{3a}: An increase in abnormal trading volume results in an increase in abnormal return volatility across all SEO types.

H_{3b}: Firms in low-performing sectors will experience a higher level of abnormal return volatility, compared with that of high-performing sectors during periods of increasing information asymmetry.

3.4.1.2 SEO Discount

The SEO discount is measured as the difference between the previous day closing price and the SEO announcement offer price (Asem et al. 2016). The SEO discount plays a key role in the number of subscriptions, which varies across countries. For example, on average, rights issues result in an 8.3% discount in the US (Armitage 2000), 17% in Britain (Slovin, Sushka & Lai 2000) and 19% in Australia (Owen & Suchard 2008). Moreover, discounts vary across each SEO type, with private placements providing, on average, a 7% discount (Xu, S, How & Verhoeven 2017) and rights issues offering approximately 19% for firms in the ASX 200 (ASIC 2016).

Jain and Kini (1999) found that a larger offer discount is associated with a decrease in firm performance, indicating a higher degree of uncertainty. The fact that a higher discount indicates greater uncertainty about a firm’s future performance highlights a lower degree of investor sentiment and therefore a higher degree of volatility. Lei and Yucan (2016) examined this relationship for stocks listed on the Shanghai and Shenzhen stock exchange during 2007–2014. They found a positive association between the SEO discount and stock return volatility. Nonetheless, the limitation of their study is that it fails to differentiate the volatility effects of each SEO method. Because the discount offered by each SEO method can significantly vary, it is expected that their impact on volatility will also vary accordingly. Specifically, this thesis posits that a larger SEO discount is usually offered by firms with lower financial performance, which leads to decreased sentiment and increased volatility (Certo, Holcomb & Holmes 2009; Daily et. al 2003; Jain & Kini, 1999). Patel, Emery and Lee (1993) asserted that low-performing firms tend to raise larger amounts of equity to continue their operations and thus prefer combined SEOs for these allow firms to raise more capital than do standalone SEOs. Given that combined SEOs typically offer larger SEO discounts, firms that use these SEO types are expected to experience higher levels of abnormal return volatility.

Moreover, this thesis also posits that an increase in the SEO discount has a larger effect on abnormal return volatility in high- and moderate-performing sectors, compared with that in low-performing sectors. This proposition is developed according to previous findings that investors tend to be more sensitive to SEO announcements by firms in high-performing sectors. This is because a larger SEO discount is perceived to be a negative signal to investors for it indicates that the firm is overvalued, resulting in negative returns (Lei & Yucan 2016). Black's (1976) leverage effect shows that the compounding of negative returns can result in higher levels of return volatility. Thus, a positive association is expected between the SEO discount and abnormal return volatility. Thus, the following hypotheses is proposed:

> *H_{4a}: An increase in the SEO discount has a larger effect on abnormal return volatility for combined SEOs than for standalone SEOs and private placements.*
>
> *H_{4b}: An increase in the SEO discount has a larger effect on abnormal return volatility in high- and moderate-performing sectors compared with that of low-performing sectors.*

3.4.1.3 Stock Illiquidity

A positive relationship between stock illiquidity and return volatility has been widely documented across both emerging and developed markets (Amihud & Mendelson 1986; Brennan & Subrahmanyam 1996; Datar, Naik & Radcliffe 1998; Hasbrouck 1993; Ho et al.

2005). With respect to SEOs, Asem, Chung and Tian (2016) reported that this positive relationship continues to hold during SEO announcements. Qian (2011) specifically studied the changes in stock liquidity around private placements and confirmed there is a positive relationship between stock illiquidity and return volatility. As a result, if a firm issues an SEO during periods of low stock liquidity, shareholders will require a greater level of compensation, that is, a larger price discount. If investors are unable to obtain it, they may either not subscribe to the SEO or try to sell their holdings prior to the SEO (if they are already holding shares). This opportunity to sell can instigate abnormal levels of volatility because investors believe that it will be more difficult to sell their shares when there is lower liquidity after the equity raising has taken place (Amihud & Mendelson 1986; Kyle 1985). This is because when there are a large number of sell orders for a share and not enough buyers (low liquidity) to fill the orders, the share price dips rapidly, which can increase abnormal return volatility. With respect to SEOs, this thesis predicts that a decrease in stock liquidity will instigate abnormal return volatility in all SEO types. This is because regardless of which SEO type a firm chooses, investors always dislike illiquidity.

With respect to ASX sectors, a disproportionately larger number of buy or sell orders (low stock liquidity) is typically observed in high-performing sectors for there are a larger number of shareholders who simultaneously trade (buy or sell) in the same direction, and thus, higher levels of volatility are expected (Chebbi, Ammer & Hameed 2021). Hence, the following hypotheses are postulated with respect to stock illiquidity:

> *H_{5a}: An increase in stock illiquidity results in an increase in abnormal return volatility across all SEO types.*

> *H_{5b}: An increase in stock illiquidity has a larger effect on abnormal return volatility in high-performing sectors, compared with that in low-performing sectors.*

3.4.1.4 Information Asymmetry

Leland and Pyle (1977) proposed the theory of asymmetric information, which contends that there is an imbalance of information between the issuing firm and its investors. Numerous subsequent studies have supported this theory (Baron 1982; Beatty & Ritter 1986; Loughran & Ritter 2002; Ritter & Welch 2002; Rock 1986). This lack of transparency between the firm and investors is a primary driver of the observed post-announcement negative returns, which, in turn, may result in increased stock return volatility. Allen and Faulhaber (1989) and Ibbotson (1975) presented similar findings, namely, that reputable firms tend to under-price their equity issues to signal their future prospects. The firm aims to *leave a good taste in the mouth* of investors such that it can offer future SEOs at higher prices. Shroff et al. (2013) and Chae (2005) examined how information disclosures affect the degree of information asymmetry of US firms. The authors employed the average bid–ask spread and analyst forecasts as proxies for information asymmetry. A larger bid–ask spread indicates an increased degree of information asymmetry. Although information asymmetry will affect all SEO types, some variation can still be expected across each type. Chemmanur et al. (2009) found that institutional investors typically would gather information about a firm before they purchase shares in an SEO in order to gain an edge over retail investors. Therefore, the level of information asymmetry is expected to be higher in SEOs with an institutional component that can allot institutional investors large pools of shares (Cronqvist & Nilsson 2005; Krishnamurthy et al. 2005; Wu 2004). Examples include restricted (private placement) and combined SEOs (placement & non-renounceable rights issue, placement & renounceable rights issue and placement & SPP). In the case of Australian sectors, information asymmetry is expected to have a larger effect on abnormal return volatility in low-performing sectors than in high-performing sectors. This is because firms in low-performing sectors tend to have less information disclosures, which can result in increased information asymmetry (Cheng, Courtenay & Krishnamurti 2005). This effect can reduce firm value and may thus lead to reduced investor confidence, resulting in increased abnormal return volatility (Merton 1987). Consequently, it is hypothesised that:

> *H_{6a}: An increase in information asymmetry results in a higher level of abnormal return volatility for SEO types consisting of an institutional component, that is, restricted and combined SEOs, compared with that for SEO types without a dedicated institutional component (i.e. standalone SEOs).*

> *H_{6b}: An increase in information asymmetry results in higher abnormal return volatility for firms in low-performing sectors than for those in high-performing sectors.*

3.4.1.5 Disclosure of Market-sensitive Announcements

ASX (2021f, p. 1)[13] considers an announcement to be market sensitive if 'a reasonable person would expect the information to have a material effect on the price or value of the entity's securities', under ASX listing rule 3.1A. When an announcement is released, the ASX screens it and automatically classifies the announcement as a market-sensitive or non-market-sensitive one. Morningstar provides a summary of these classifications.[14] O'Shea et al. (2008) compared the effects of market-sensitive and non-market-sensitive announcements on the stock return volatility of ASX-listed firms. Unsurprisingly, they found that the former announcements had a larger impact on volatility than the latter. They also documented that the effect of market-sensitive announcements remains significant across firms, regardless of size or type. Similarly, Prasad, Bakry and Varua (2020) highlighted that an increase in the number of market-sensitive announcements will increase stock return volatility, both at the market and at the sectoral

[13] ASX listing rule 3.1 provides further clarification on how announcements are classified as market sensitive.
[14] https://datanalysis.morningstar.com.au/licensee/datpremium/html/ASX_Announcements_Onesheet.pdf

levels. They also confirmed statistical significance for other market-sensitive announcements in addition to those for SEOs, such as for takeovers, acquisitions/disposals, periodic and progress reports, stock exchange announcements and firm administration. Since investors are typically reactive to these announcements, this research includes the number of market-sensitive announcements released within the 6 months leading up to an SEO announcement as a variable. The 6-month period is chosen since ASX 200 listed firms do not issue SEOs more than once in 6 months. Therefore, this period is the longest duration that market-sensitive announcements can be captured leading up to the SEO announcement in order to prevent information spillover from a previous SEO announcement.

Following on from this discussion, it is expected that SEO types with a larger number of market-sensitive announcements in the 6 months leading up to the SEO will experience higher levels of abnormal return volatility. Seamer (2014) and North (2011) found that at the sectoral level, firms of low-performing sectors are less likely to meet their continuous disclosure obligations, which results in a lower number of market-sensitive announcements from these firms. Moreover, firms from these low-performing sectors do disclose information, it is usually only 'material' market-sensitive disclosures, which elicit a larger shareholder reaction (Brown, Kwan & Wee 2006). Thus, it is expected that if these sectors release these 'material' disclosures within the 6 months leading up to an SEO, it will instigate higher levels of abnormal return volatility than that of high-performing sectors. Therefore, the following hypotheses are proposed:

> *H_{7a}: Firms who use SEO types associated with a larger number of market-sensitive announcements in the 6 months leading up to the SEO announcement, will experience higher abnormal return volatility.*

H_{7b}: Low-performing sectors experience higher abnormal return volatility than high-performing sectors, in response to market-sensitive announcements.

3.4.1.6 Corporate Insider Trading Behaviour (Disclosure of Shareholdings)

Corporate insider trading behaviour functions as a signal to market participants whether stock prices will fall or rise. Since corporate insiders are required to disclose their trading behaviour to the ASX, market participants view this action as a bullish or bearish signal depending on whether these insiders buy or sell shares, which usually translates into increased levels of stock return volatility (Hable 2021). This effect is partly attributable to investors' assumption that corporate insiders have privileged knowledge about internal operations and any intentions of future capital raising by the firm (Ching, Firth & Rui 2006; Lang & Lundholm 2000). As regards SEOs, it is not uncommon to observe corporate insiders changing their net positions surrounding the SEO announcement (Clarke, Dunbar & Kahle 2001; Gombola, Lee & Liu 1999). Karpoff and Lee (1991), Kahle (2000) and Cziraki, Lyandres and Michaely (2019) provided comparable results, noting that corporate insider selling increases before SEOs.

The extent of the effects of this trading behaviour disclosure (via ASX disclosures, such as Appendix 3Y[15] and Form 604[16]) during the SEO on abnormal return volatility would depend on the SEO type that is issued and the sector in which the firm operates. Since a private placement involves only institutional shareholders, it is expected to instigate the highest levels of volatility (Wang, SS & Xu 2014), because they are the only investor type being offered shares, resulting in them purchasing large blocks of shares (Hertzel & Smith 1993). Schwert (1990) argued that the demand for such a large parcel of shares at a single point in time is expected to elicit high levels of volatility. Since combined and standalone SEO types are not

[15] https://www.asx.com.au/documents/rules/Appendix_03Y.DOC
[16] https://asic.gov.au/regulatory-resources/forms/forms-folder/604-notice-of-change-of-interests-of-substantial-holder/

restricted to institutional shareholders, the volatility for firms using these SEO types is expected to be less. With respect to ASX sectors, corporate insider trading is expected to be more actively undertaken in high-performing sectors since their share prices typically experience larger price run-ups leading up to the SEO announcement and larger price drops afterwards. Accordingly, this research argues that market participants may expect corporate insiders to take advantage of the higher prices in these sectors before the SEO announcement, which may instigate higher levels of abnormal return volatility. Hence, the following hypotheses are specified:

> *H_{8a}: Corporate insider trading has a larger effect on a firm's abnormal return volatility that uses restricted SEOs, compared with that of combined and standalone SEOs.*
>
> *H_{8b}: Corporate insider trading results in higher abnormal return volatility for firms operating in high-performing sectors than for those in low-performing sectors.*

3.4.2 Firm-specific Factors

3.4.2.1 Cost of Equity Capital

The cost of equity capital is defined as the theoretical return that firms are expected to provide their shareholders to compensate for the risk associated with investing in the firm. It is usually paid in the form of dividends and capital growth over the life of the investment. Since a firm's cost of equity capital is usually higher than the cost of debt, using equity (i.e. issuing shares) would theoretically not be the ideal choice to raise capital (Myers & Majluf 1984). However, the dividend imputation system launched in Australia in 1987 has played a significant role in reducing the cost of equity capital for firms and in reducing tax implications (through franking credits on dividends) for shareholders (Ainsworth et al. 2016). Using equity financing allows ASX firms to replenish their balance sheets quickly during economic disruptions, which minimises their chances of going into voluntary or involuntary administration. Therefore, the fact that monetary benefits flow to both the firm and their shareholders has led to a lower cost of equity capital financing, thereby increasing the popularity of using SEOs in the capital-raising process (Pattenden 2006; Zhou et al. 2016).

Zhang (2014) studied the impact of the cost of equity capital on SEOs for US listed firms and found that firms that have a higher cost of equity capital tend to experience a larger negative reaction to SEO announcements, which translates to higher levels of volatility. Duffee (1995) also posited that the negative reaction to SEO announcements is exacerbated when firms are in financial distress, resulting in a larger increase in volatility. Since firms typically experience financial distress during economic disruptions, especially those with a high cost of equity capital, it is expected that firms issuing SEOs are likely to experience abnormal levels of volatility. For the case of each SEO type, it is expected that those consisting of rights issues will result in a higher cost of equity capital. This is because rights issues are characterised by higher retail shareholder participation rates, resulting in firms incurring a higher cost of equity capital (Au Yong et al. 2021). This is because retail shareholders have a lower risk tolerance and purchase a smaller number of shares, compared with institutional shareholders, and therefore expect a higher rate of return on their investment per share (Attig et al. 2013; Kannadhasan 2015). Thus, as mentioned previously, W Zhang (2014) highlighted that the increase in this cost of equity capital translates into higher levels of volatility.

With respect to sectors, an increase in a firm's cost of equity capital is expected to result in higher abnormal return volatility for firms in low-performing sectors. This relationship is expected is because in high-performing sectors, shareholders accept a greater level of risk when participating in SEOs, which leads to a higher cost of equity capital and thus higher volatility. In contrast, in low-performing sectors, shareholders do not expect a high degree of risk, and thus, firms will incur a lower cost of equity capital and lower volatility (Verrecchia 1999). As a result, the following hypothesis is proposed:

H_{9a}: An increase in the cost of equity capital for issuing SEOs consisting of rights issues results in higher abnormal return volatility, compared with that of SEO types without a rights issue component.

H_{9b}: An increase in the cost of equity capital results in higher abnormal return volatility for firms in high- and moderate- (low-) performing sectors.

3.4.2.2 Market-to-Book Value

The adverse selection theory states that a firm tends to undertake SEOs when its stock price is overvalued (Myers & Majluf 1984). Therefore, it is natural to assume that investors will downgrade their valuation of the firm's stock price after an SEO owing to the increased supply of shares. Accordingly, the downgraded price will cause the market-to-book value to decrease, because the market value falls closer towards the book value. Loughran and Ritter (1997) examined the changes in operating performance of firms after undertaking an SEO in 1979–1989, for NYSE, AMEX and NASDAQ stocks. They documented an average decrease in the market-to-book value from 1.98 to 1.42 across all stocks following the SEO announcement. Although this value indicated that the firm was still slightly overvalued, this finding is consistent with the claim that investors downgrade the firm's value following an SEO (Carlson, Fisher & Giammarino 2006; Kim & Purnanandam 2006; Korajczyk, Lucas & McDonald 1989; Liu, J et al. 2016; Masulis & Korwar 1986).

Firms with high market-to-book value ratios usually provide high growth and provide superior returns in the short run compared with those with low ratios (DeAngelo, DeAngelo & Stulz 2010). This is because investors usually bid up the price of the stock, in anticipation that it will deliver promising returns in the future. This attracts more investors during SEOs because when their overvalued stocks appear to be issued at a seemingly attractive discount, investors willingly participate in the offering. The rush of investors to chase a higher return at a higher discount because of the ‘fear of missing out’ is expected to drive up demand and increase the abnormal return volatility during an SEO (Chen, J, Chollete & Ray 2010). Fama and French (1995) also showed that, in addition to higher returns, firms with high market-to-book value ratios will experience higher levels of volatility. With respect to the effect on each SEO type, it is anticipated that institutional and retail investors would both chase such firms since both investor types naturally seek higher returns. Thus, an increase in this ratio is expected to instigate abnormal return volatility across all SEO types. However, from a sectoral perspective, since high market-to-book value ratios are associated with high-return firms, it is expected that high-growth sectors would experience higher abnormal return volatility in response to an increase in this ratio. Thus, the following hypotheses are proposed:

> *H_{10a}: An increase in the market-to-book value has a similar effect on the abnormal return volatility of all firms, irrespective of the SEO type chosen.*

> *H_{10b}: An increase in the market-to-book value has a larger effect on abnormal return volatility for firms in high-performing sectors, compared those in low-performing sectors.*

3.4.2.3 Firm Size

The finance literature and accounting literature have highlighted that firm size is negatively associated with returns and volatility (Banz 1981; Drew 2003; Reinganum 1982). The lower volatility stems from the investor belief that the future performance of larger firms is less uncertain and that these firms will face minimal financial distress (Chan, KC & Chen 1991; Chen, N & Zhang 1998; Fama & French 1992; Vassalou & Xing 2004). This expectation is driven by the facts that larger firms have larger cash reserves, easier access to financing and higher demand for human capital (Finkle 1998). Since these firms are associated with less risk, investors are more likely to partake in their SEOs (Loughran & Ritter 1997). Moreover, since investors also understand that larger firms tend to have higher liquidity and would experience a lower level of investor dilution, which would thus minimise their exposure to large post-announcement negative returns, resulting in lower levels of volatility (Barnes & Walker 2006). Accordingly, it is expected that during the entire sample period, an increase in firm size will reduce return volatility across all SEO types. Thus, the following hypothesis is proposed:

H_{11a}: An increase in firm size induces less-than-normal volatility in all SEO types.

However, this relationship is not expected to hold during an economic disruption. In this case, it is expected that larger firms that choose SEO types that do not offer benefits and flexibility to shareholders will be most heavily penalised by shareholders, manifesting through abnormal return volatility. This is because shareholders expect larger firms to be safer investments during economic disruptions because they have large cash reserves to help them navigate through turbulent periods (Arslan, Florackis & Ozkan 2006; Fort et al. 2013; Jebran et al. 2019). However, if larger firms undertake an SEO during economic disruptions, their shareholders view it as a negative signal (Elyasiani, Mester & Pagano 2014). Moreover, since larger firms are considered safer investments, if they use an SEO type that limits a shareholder's benefits and flexibility, the firm is penalised by shareholders for these decisions, translating into abnormal levels of volatility. These types include standalone non-renounceable rights issues and private placements, which are therefore expected to instigate the highest levels of volatility. In the case of non-renounceable rights issues, retail and institutional shareholders are left to compete for shares (with institutional shareholders usually acquiring a larger portion of the SEO), leaving retail investors with no opportunity to participate. Moreover, shareholders view *non-renounceability* on shares negatively because it does not allow them to sell their right, and they forfeit any entitlement they do not use (Balachandran et al. 2008). With respect to standalone private placements, they not only result in the greatest ownership dilution for retail shareholders but are also more commonly used by smaller firms (Marciukaityte, Szewczyk, &

Varma 2005). Thus, if larger firms were to use this SEO type during an economic disruption, they will be more heavily penalised. Standalone renounceable rights issues are also expected to instigate volatility, but to a lesser extent. This is because they are viewed more favourably by shareholders as these issues offer renounceability, allowing shareholders to sell their rights in the open market and thus minimise the effects of ownership dilution (Balachandran et al. 2008). Last, combined SEOs (placement & non-renounceable rights issue, placement & SPP and placement & renounceable rights issue) are expected to instigate the lowest levels of volatility since they consist of separate share allocations for institutional investors and retail investors, which ensures the greatest level of fairness between both these shareholder types (Dennis & Strickland 2002; Gabaix et al. 2006; Sias 1996, Xu, Y & Malkiel 2003). Thus, a firm's shareholders will penalise larger firms (through higher levels of volatility) that use more restrictive and less flexible SEOs (private placements, and non-renounceable rights issues), and these firms will experience higher levels of volatility than larger firms that use more flexible and beneficial SEOs (combined SEOs). Consequently, the following hypothesis is proposed:

> *H_{11b}: Larger firms that choose SEO types with greater shareholder restrictions (non-renounceability) and less fairness (standalone SEOs) during economic disruptions, experience higher abnormal return volatility than do larger firms that choose SEOs with greater flexibility (renounceability) and more fairness (combined SEOs).*

With respect to the ASX sectors, investors typically prefer to invest in high-performing sectors because they provide superior returns, but there is also higher risk with doing so (Narayan, Ahmed & Narayan 2017). Therefore, to minimise this risk, investors prefer to invest in larger firms because their returns are not as volatile (Reinganum & Smith 1983). According to these preferences, investors will always find it more attractive to find an investment that provides the ideal mix of high returns and low risk. With specific reference to SEOs, to obtain this ideal mix, it would be expected that investors would be more likely to participate in SEOs issued by larger firms (lower risk) in high-performing sectors (higher return). Since SEOs can provide this mix at a discounted price, investor participation is expected to be higher in high-performing sectors, which will instigate higher levels of abnormal return volatility compared with that in low-performing sectors. Thus, the following hypotheses are proposed:

H11c: Larger firms in high- and moderate-performing sectors experience higher abnormal return volatility, compared with larger firms in low-performing sectors.

3.4.3 Market Factors

Aggregate Market Volatility

It is important to account for the effect of aggregate market volatility on abnormal return volatility during SEOs, since it affects the ability of firms to raise equity. Schill (2004) examined the market volatility when firms undertook equity raising during volatile periods. The author found a 13% decrease in the number of equity take-ups by investors during periods of higher market volatility. For firms that do raise equity in a volatile market, the amount of capital raised is 21% less than that in a calm market. The significant decline in the proceeds is an indication of investor uncertainty. More recently, the 2008 GFC and the COVID-19 pandemic proved that although firms can still raise equity during economic disruptions, it can result in a lower quantity of subscriptions owing to the heightened aggregate market volatility. Sharma, Narayan and Zheng (2014) suggested that this aggregate market volatility can trickle down and affect the volatility of individual stocks. In contrast, Campbell et al. (2001) highlighted that although there is such a correlation between individual stocks and the overall market, it is weak. This is because individual stocks experience larger swings in volatility than the overall market. However, during periods of economic disruptions, the correlation tends to become stronger as individual stocks move in line with general declines in the overall market.

This relationship is expected to hold across all SEO types and sectors. Hence, the following hypothesis is proposed:

> *H_{12a}: An increase in the aggregate market volatility will elicit a similar effect on abnormal return volatility across all firms irrespective of the SEO types chosen.*

> *H_{12b}: An increase in the aggregate market volatility will have a similar effect on abnormal return volatility in firms across all sectors.*

Each of the 12 proposed hypotheses have been developed to support the four key contributions of the thesis covered in Section 1.3.2 of Chapter 1. The four contributions include:

1. Examination and measurement of the extent to which SEOs instigate and perpetuate abnormal return volatility for ASX 200 listed firms using the traditional AVAR proxy.

2. Improvement of the accuracy of the traditional AVAR abnormal return volatility proxy by accounting for volatility clustering and other stylised features of stock return volatility (i.e. heteroscedasticity and a leptokurtic distribution) using the GARCH and GJR-GARCH specifications.

3. Challenging the assumption that all SEO types homogeneously affect return volatility of Australian firms by examining abnormal return volatility across *each SEO type* and uncovering their determinates, to ascertain their idiosyncratic impact on abnormal return volatility.

4. Comparatively examine how SEOs instigate abnormal return volatility across the aggregate market relative to a sectoral basis. The disaggregation by sectors will

help to account for the distinct ‘two-speed’ Australian economy, consisting of both high and low-performing sectors.

3.5 Summary

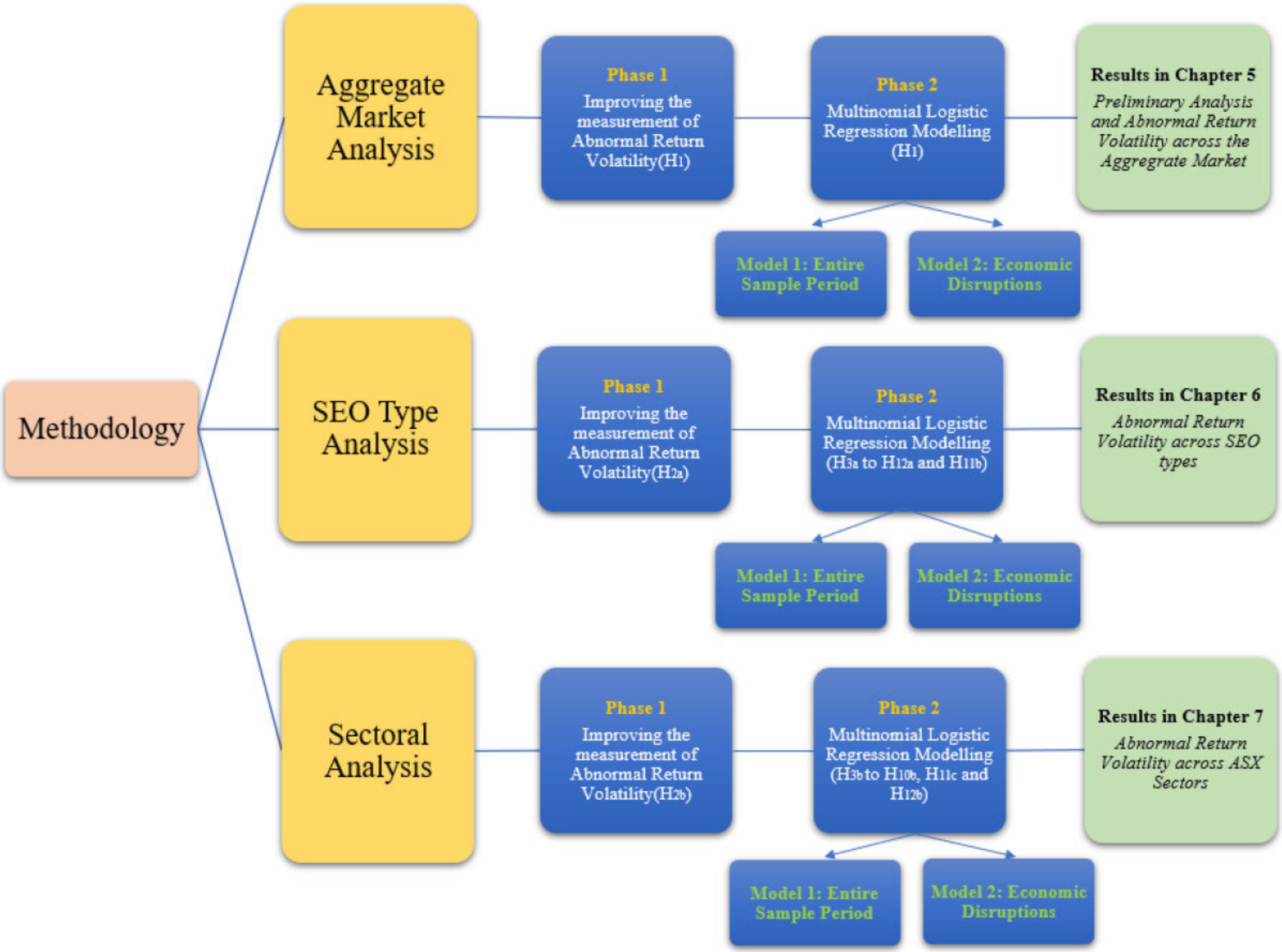
This chapter presented an in-depth examination of the studies relevant to the measurement of abnormal return volatility and its potential determinants. The first section reviewed studies about the overall reaction of investors to SEO announcements and found that the reaction was quite negative. The next section then discussed the existing measures of abnormal return volatility and challenged their accuracy. The third section identified factors that potentially explain the changes in abnormal return volatility during SEOs, and the last section discussed the contributions to the literature that this thesis provides. The next chapter discusses the methodology used to address the hypotheses from this chapter. A detailed discussion of the data sources and their empirical specifications are also provided.

Chapter 4: Methodology, Data Sources and Description

4.1 Introduction

This chapter provides a detailed explanation of the methodology implemented and the data sources used to address the objectives of this thesis. A summary of the steps involved in the methodology are presented in Figure 4.1, which details the hypotheses covered in each phase of testing. Section 4.2 presents the empirical models employed, the measurement of the dependant and independent variables and the robustness tests applied. Section 4.3 discusses the robustness tests, and Section 4.4 summarises the data sources for the variables used, the collection methods, the selection criteria and the study period chosen for the thesis. Section 4.5 explains the preliminary tests undertaken to check for multicollinearity and unit root within the data, and Section 4.6 concludes the chapter.

Figure 4.1: Mapping of Methodology and Results



4.2 Methodology

4.2.1 Phase 1: Improving the Measurement of Abnormal Return Volatility

In Phase 1 of this thesis, an event study has been adopted to measure the changes in abnormal return volatility surrounding the days of each SEO announcement. Introduced and popularised by Ball and Brown (1968) and Fama et al. (1969), event studies have been used as the core method to study investor reactions (through stock price reactions) to capital market announcements. Initially, the event study methodology was used to measure event-induced (abnormal) *returns* around market events, but has since been extended to also measure event-induced *volatility* (Savickas 2003). This research leverages this technique to measure the presence of abnormal return volatility (*AVAR*) during the SEO announcement event window. GARCH effects were also incorporated as part of the *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies to account for the time-varying nature of volatility in stock returns, resulting in the improvement in its accuracy. Last, this procedure was performed for the aggregate market, each SEO type and each Australian sector.

The event window that was specified follows Veld et al. (2020), who performed a meta-analysis of studies that focused on the SEO announcement effects across multiple countries. In Australian financial markets, substantial price changes were observed during the [−15, +15] day event window. The same event window was adopted by similar studies as described in the meta-analysis (Balachandran et al. 2009; Sault et al. 2015). Therefore, this thesis employed the [−15, +15] day event window to measure the average *AVAR* during SEO announcements. This event window description was also used for two additional reasons. First, rather than the largest price changes occurring at the point of actual distribution of the shares, the largest fluctuations are observed during the days surrounding the SEO announcement (Balachandran et al. 2009; Sault et al. 2015; Veld, Verwijmeren & Zabolotnyuk 2020). Second, since ASX firms cannot undertake multiple SEOs during the [−15, +15] event window, the chosen event window eliminates bias in the estimation process, whereby *AVAR* may be overstated because of multiple SEOs issued in one event window. This is because for ASX-listed firms, the average time between the date of the SEO announcement and the physical distribution of shares to each shareholder is approximately 2–3 months (Brown et al. 2009).

4.2.2 Phase 2: Multinomial Logistic Regression Modelling

Phase 2 employed an MLR modelling technique to understand the determinants of the abnormal return volatility observed during the SEO announcement event window. Although fixed and random effect regressions or generalised method of moments regressions are widely used in financial asset analyses of panel data, these methods are only appropriate when trying to explain the effect of a one-unit change in the independent variable on the dependant variable while accounting for the inherent characteristics of financial asset returns and volatility (e.g. endogeneity, exogeneity and heteroscedasticity). However, these methods are not appropriate in this thesis because although abnormal return volatility is a continuous variable (a variable that can take any value between 0 and infinity), it is commonly expressed as a range (e.g. 0 to 1, 1 to 2, > 3) to allow for a more meaningful interpretation (Ahmed, Bradford & Bloch 2020; DeFond, Hung & Trezevant 2007; Landsman & Maydew 2002; Landsman, Maydew & Thornock 2012; Truong 2012). Thus, the dependant variable was specified as a categorical variable defined by a given range, which is further discussed in Section 4.2.2.2.1. For this reason, the MLR modelling technique was found to be the most appropriate.

Moreover, when panel data are used, it would be ideal to use a fixed effects-MLR approach. However, this approach was not appropriate for this thesis because it requires that all explanatory variables experience variation *within* each panel, that is, in each 31-day event period. However, this research used a continuous variable (‘market-sensitive announcement’) that does not vary *within* the panels but instead only varies *across* panels. Since this variable captures important phenomena related to volatility around the SEO announcement, its omission may lead to omitted variable bias. Last, researchers consider MLR useful because it does not require normality, linearity or homoskedasticity in the dataset (Bayaga 2010). Hence, many preliminary tests on the data do not need to be performed to ascertain their appropriateness for the model. Nevertheless, for the purpose of completeness, unit root tests and multicollinearity tests are still undertaken to gain insights into the nature of the data.

To model the relationship between abnormal return volatility (as a categorical variable) and its determinants effectively, this research used a *pooled panel* MLR model. This model belongs to the generalised linear model family of models popularised by McCullagh and Nelder (2019). MLR allows the *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies to be grouped into categories defined by a range either between 0 and 1 or greater than 1. These categorisations allow the model to capture the relative risk ratio (RRR) (i.e. the probability) of a firm to experience either less-than-normal volatility (RRR < 1) or abnormal return volatility (RRR > 1) in response to changes in each of the determinants.

4.2.2.1 Empirical Model

Two empirical models (Model 1 and 2) were estimated across the aggregate market, each SEO type and each sector. Model 1 is the base model, which examined the impact of various determinants on abnormal return volatility across the entire sample period. Model 2 is the secondary model, which estimated the effect of various determinants on abnormal return volatility exclusively during economic disruptions. For both models, the improved abnormal return volatility proxies (*AVAR–GARCH* and *AVAR–GJR–GARCH*) from Phase 1 were used as the dependant variable in the regression models within Phase 2.

It should be noted that some SEO types and sectors were excluded from the estimation process, because of an insufficient number of observations to yield reliable and meaningful results, or because of a lack of SEOs issued during economic disruption periods (see Appendix 1). The SEO types for which Models 1 and 2 were not estimated include bonus issues, renounceable & non-renounceable issues and standalone SPPs. With respect to the ASX sectors, Models 1 and 2 were not estimated for the Utilities and Communication Services sectors. The lack of observations for these sectors is likely because they both operate on a low degree of equity capital because most firms in these sectors do not usually require extra funding. Moreover, consumer demand for these sectors remains relatively consistent during economic expansions and disruption periods. Hence, equity funding via SEOs is not a necessity. Models 1 and 2 (see Sections 4.2.2.2 and 4.2.2.3, respectively) were both employed across all the remaining SEO types and sectors. Model 1 was used to examine the impact of various SEO-specific, firm-specific and market-wide factors on abnormal return volatility across the entire sample period. In contrast, Model 2 was used to examine the impact of these factors on abnormal return volatility during economic disruptions only.

4.2.2.2 Model 1: Base Model (Entire Sample Period)

$$AVAR\text{–}GARCH_{i,t} = \beta_0 + \beta_1 AVOL_{i,t} + \beta_2 DISC_{i,t} + \beta_3 ILLIQ_{i,t} + \beta_4 BAS_{i,t} + \beta_5 MSA_i + \beta_6 CIT_i + \beta_7 COE_{i,t} + \beta_8 MBV_{i,t} + \beta_9 SIZE_{i,t} + \beta_{10} DIS_{i,t} + \beta_{11} AMV_t + \varepsilon_{i,t} \qquad (1)$$

where:

$AVAR\text{–}GARCH_{i,t}$ = the abnormal return volatility of firm i on day t of the event period [−15, +15],

$AVOL_{it}$ = the abnormal trading volume of firm i on day t of the event period,

$DISC_{it}$ = the SEO discount of firm i on day t of the event period,

$ILLIQ_{it}$ = the stock illiquidity of firm i on day t of the event period,

BAS_{it} = the bid–ask spread of i on day t of the event period,

MSA_i = the number of market-sensitive announcements released by firm i in the 6 months leading up to the event period,

CIT_i = a dummy variable that carries the value of 1 if firm i had any corporate insiders trading their shares during the 31-day event period, and 0 otherwise,

COE_{it} = the cost of equity capital of firm i on day t of the event period,

MBV_{it} = the market-to-book ratio of firm i on day t of the event period,

$SIZE_{it}$ = the firm size of firm i on day t of the event period,

DIS_{it} = a dummy variable that carries the value of 1 if firm i announced an SEO during an economic disruption (i.e. the dot-com bubble, the GFC or the COVID-19 pandemic), and 0 otherwise, on day t of the event period,

AMV_t = the aggregate market volatility of the ASX 200 Index on day t of the event period,

$\varepsilon_{i,t}$ = the error term.

The definition and measurement of each variable included in the model will be discussed in the succeeding subsection.

4.2.2.2.1 Measurement of the Dependant Variable: Abnormal Return Volatility (*AVAR–GARCH* and *AVAR–GJR–GARCH*)

The term *AVAR* originates from Beaver (1968) and was widely promoted by Landsman and Maydew (2002) and DeFond, Hung and Trezevant (2007). It stands for ‘abnormal return variance' or 'abnormal return volatility'. To determine *AVAR*, the market model for the abnormal returns of each stock was first specified using Sharpe's (1964) capital asset pricing model:

$$\mu_{i,t} = R_{i,t} - (\alpha_i + \beta_i R_{market}) \qquad (2)$$

where $\mu_{i,t}$ is the abnormal return of firm *i* for the event window *t*; $R_{i,t}$ is the natural log of the return of firm *i* for the event window *t*; and R_{market} is the return of the ASX 200 Index during the event window *t*. The variables α_i and β_i are the market model parameter estimates. Following Landsman and Maydew's (2002) specification, $AVAR_{i,t}$ is defined as follows:

$$AVAR_{i,t} = \frac{\mu_{i,t}^2}{\sigma_i^2} \qquad (3)$$

where $AVAR_{i,t}$ is calculated for the event window t, and $t = [-15, +15]$ in relation to announcement day 0, which is the event day for firm *i*. The variable, $\mu_{i,t}^2$ refers to firm *i's* average squared abnormal returns during the event window *t*, and σ_i^2 is the variance of the market model returns of firm *i* during the 245 day estimation window [−260 days to −15 days]. The 245 day estimation window reflects the average number of trading days in one calendar year, which exceeds the recommended minimum of 100 days (Armitage 1995; Park 2004). A larger estimation window was specified to improve the accuracy of the average volatility estimate. An $AVAR_{i,t}$ value between 0 and 1 indicates that the firm experienced less-than-normal return volatility during the SEO event window. A value of 1 indicates that the SEO event did not have any abnormal (i.e. normal) effect on return volatility. Last, a value that exceeds 1 indicates that the firm experienced an abnormal level of return volatility during the SEO event window. As an example, a value of 0.5 indicates that the firm experienced half of the normal volatility and a value of 2 indicates that the firm experienced double the normal volatility and therefore is deemed abnormal.

The limitation of the traditional *AVAR* measure is that it uses the standard variance measurement of σ_i^2, which assumes that each period's variance is independent. Consequently, it does not accurately capture volatility clustering, which is an important stylised feature observed in stock return volatility (Tsay 1987). This problem can be solved by using conditional variance (h_i) in its place, which is captured by a GARCH specification (Bollerslev 1986). This specification assumes that the previous period variance will determine the current period variance, thereby improving its accuracy (Alberg, Shalit & Yosef 2008; Bollerslev 1986). This means that if the previous period volatility is high (low), the current period volatility will also be high (low). Mandelbrot (1963) highlighted that the use of conditional variance is appropriate because volatility is, in fact, time-varying and retains a memory of prior volatility shocks (i.e. volatility clustering). Moreover, the volatility of stock returns tends to exhibit specific stylised properties, namely, heteroscedasticity and leptokurtosis, which the existing measure does not account for. Therefore, GARCH effects (h_i) were incorporated into the *AVAR* proxy, which includes a one-period lag within the GARCH model, that is, GARCH (1,1), which creates a more realistic method of measuring abnormal return volatility during SEO announcements (Alberg, Shalit & Yosef 2008; Engle & Ng 1991). The improved formula is as follows:

$$AVAR\text{–}GARCH_{i,t} = \frac{\mu_{i,t}^2}{h_i} \tag{4}$$

$$h_i = \alpha_{i,0} + \sum_{i=1}^{q} \alpha_i \varepsilon_{i,t-1}^2 + \sum_{i=1}^{p} \beta_j h_{i,t-1}^2$$

where:

h_i is the conditional variance as specified by the GARCH equation, of firm i's returns during the estimation window [–260 days to –15 days]. This substitutes the unconditional variance σ_i^2 component expressed in Equation (3).

α_i denotes size of the prior period i shocks.

$\alpha_i \varepsilon_{i,t-i}^2$ denotes the GARCH term which captures the symmetric volatility.

$\beta_j h_{i,t-1}^2$ is a parameter that captures the persistence of volatility.

$\alpha_0, \alpha_{i,j}$ and β are non-negative parameters with $\alpha > 0$ to ensure that the conditional variance remains positive.

Moreover, the asymmetric impact of bad news relative to good news on return volatility is also typically observed in stock returns. Figure 4.2 shows that negative shocks tend to elicit a larger impact on the size of return volatility than do positive shocks (Engle & Ng 1993). Prior research indicated that this is because bad news causes shareholders to have a larger negative reaction than does good news, which translates into higher levels of volatility; known as the 'leverage effect' (Engle & Ng 1993; Glosten, Jagannathan & Runkle 1993; Nelson 1991; Yu 2005).

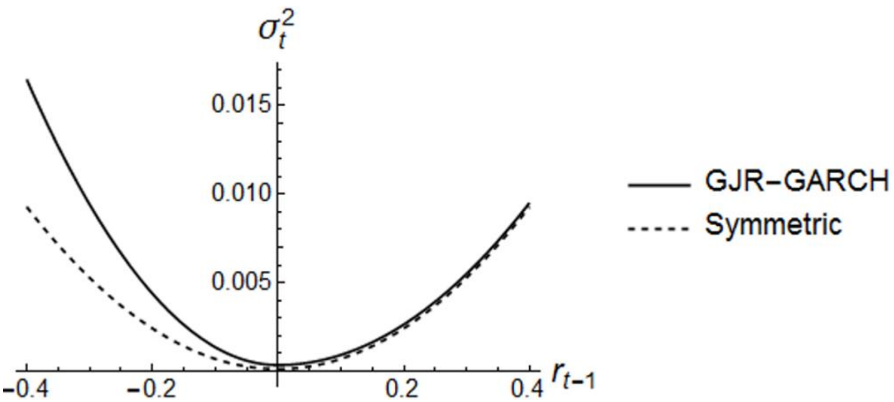


Figure 4.2: Comparing GARCH (Symmetric) and GJR–GARCH (Asymmetric) News Impact Curves (Source: Jiang & Xia 2018)

Given that this study examined various SEO types, with some types being more negatively perceived by shareholders than others, leverage effects were included as part of the robustness test. To do this, the $AVAR\text{–}GARCH_{i,t}$ was further extended by employing GJR–GARCH (Glosten, Jagannathan & Runkle 1993) estimations, expressed as *AVAR–GJR–GARCH*, {Equation (5)}. This specification was also applied across each sector to determine the degree to which shareholders across specific sectors perceived SEO announcements as a negative signal, thus having a substantial effect on *AVAR*.

$$AVAR\text{–}GJR\text{–}GARCH_{i,t} = \frac{\mu_{i,t}^2}{h_i} \tag{5}$$

$$h_i = \alpha_0 + \sum_{i=1}^{q}(\alpha_1 \varepsilon_{t-i}^2 + \delta\varepsilon_{t-i}^2\, d_{t-i}) + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$$

where:

h_i denotes the conditional forecasted variance during the estimation window,

α_0 is a constant,

$\alpha_1\varepsilon_{t-i}^2$ is the GARCH term that captures the symmetric volatility,

$\delta\varepsilon_{t-i}^2 d_{t-i}$ is the leverage term which captures the effect that prior shocks have on the current conditional variance,

$\beta_j\sigma_{t-j}^2$ is a parameter that captures the persistence of volatility,

d_{t-i} is a dummy variable; d_{t-i} = 1 if ε_{t-i} < 0 (bad news), and

d_{t-i} = 0 if ε_{t-i} > 0 (good news).

The modification resulted in the development of the following measures: *AVAR–GARCH* and *AVAR–GJR–GARCH*. As mentioned previously, although these measures consist of continuous data (data that can take any value), the literature has commonly expressed abnormal return volatility as a range[17] to facilitate a more meaningful interpretation. Therefore, in this thesis,

[17] For example, an *AVAR* in the range of 0 to 1 indicates a 'less-than-normal' return volatility, and an *AVAR* greater than 1 indicates an 'abnormal return volatility'. In addition, an *AVAR* of 2 would indicate double the normal volatility and so on (Ahmed, Bradford & Bloch 2020; DeFond, Hung & Trezevant 2007; Landsman & Maydew 2002; Landsman, Maydew & Thornock 2012; Truong 2012).

each *AVAR–GARCH* and *AVAR–GJR–GARCH* observation during the event window was grouped into nominal/categorical outcomes to preserve its meaning during interpretation of the results. In line with previous studies, all values below 1 were placed into a single category (i.e. category 0, which is the base category/outcome) and were defined as 'less-than-normal volatility'. The values above 1 were defined as abnormal return volatility. However, it important to note that these values were not simply amalgamated into one category because of the wide range of *AVAR–GARCH* values above 1 in the dataset.[18] To determine the categories for the *AVAR–GARCH* values above 1, a simple and unbiased categorisation approach was adopted. First, the average (mean) of all observations with an *AVAR* above 1 was determined. This was calculated to be 3.15, which indicates that the *average* abnormal return volatility is 3.15 times the normal level of volatility. Then, the standard deviation of all observations above 1 was calculated (3.81), which was used as the increment between each category above the average of 3.15. Given that the number of observations greater than one standard deviation above the mean represents only about 5% of the sample, the remaining observations (above 6.95) were grouped together into one category. Table 4.1 provides a summary of the categories used to classify the traditional *AVAR* proxy and the improved *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies.

[18] In the dataset, there were *AVAR–GARCH* and *AVAR–GJR–GARCH* values that reached up to 90. Values this large were found to be outliers since most observations fell between the range of 1 and 50. Thus, to reduce the potential bias in the results, the events that consisted of values above 50 were removed from the dataset.

Table 4.1: Abnormal Return Volatility Categorisation

Mean (average)	3.15
Standard deviation (SD)	3.81

Description	**Range***	**Category Number**	**Category Name**	**Number of Obs.**	**Percentage (%) of Sample (All Obs.)**	**Percentage (%) of Sample (with Obs. > 1)**
Less-than-normal volatility (base outcome)	$0 > AVAR \leq 1$	0	*Less-than-normal* volatility	15,037	83.1	N/A
Abnormal return volatility (above normal but below the average)	$1 > AVAR \leq 3.15$	1	*Low* Abnormal Return Volatility	2,177	12	71.2
Abnormal return volatility (1 SD above the average)	$3.15 > AVAR \leq 6.95$	2	*Moderate* Abnormal Return Volatility	646	3.6	21.1
Abnormal return volatility (> 1 SD above the average)	> 6.95	3	*High* Abnormal Return Volatility	235	1.3	7.7
Total				**18,095**	**100**	**100**

Note. * The ranges also apply to both of the improved proxies, *AVAR–GARCH* and *AVAR–GJR–GARCH*.

4.2.2.2.2 Measurement and Definition of Independent Variables

4.2.2.2.2.1 Issue-specific factors

Abnormal Trading Volume

The abnormal trading volume ($AVOL$) was calculated following DeFond, Hung and Trezevant (2007) and Kajüter, Klassmann and Nienhaus (2016). It should be noted that in Phase 2, *AVOL* was measured on a daily basis during the event period, rather than using the average *AVOL* (which was used in Phase 1). This is because the MLR measures the daily changes in each independent variable during the event period. *AVOL* is specified as follows:

$$AVOL_{i,t} = \frac{\overline{DTV_{it(event)}}}{\overline{ATV_{i(est)}}} \tag{6}$$

where $\overline{DTV_{it(event)}}$ is defined as the daily trading volume of firm i on day t of the SEO event window, and $\overline{ATV_{i(est)}}$ is firm i's average trading volume during the 245-day estimation window [−260, −16]. An $AVOL_{i,t}$ between 0 and 1 indicates that the firm experienced less-than-normal trading volume during the SEO event window. A value of 1 indicates the firm experienced a normal level of trading volume and a value above 1 indicates that abnormal trading volume was experienced by the firm during the SEO event window.

SEO Discount

To understand how the size of the discount changes relative to the SEO announcement day, this research calculated the SEO discount on a daily basis across the event window. This was computed as a percentage difference between the SEO price and the closing price for the day of the event window (Chan, K & Chan 2014; Henry & Koski 2010). The SEO discount is expressed as follows:

$$\text{SEO Discount}_{i,t} = \frac{P(SEO)_{i,t} - P(close)_{i,t-j}}{P(close)_{i,t-j}} \tag{7}$$

where $P(SEO)_i$ is the offer price of the SEO issued by firm i and $P(close)_{it-j}$ is the closing price of firm i at time $t-j$, where t is the announcement date and j represents the number of days before/after the announcement date.

Stock Illiquidity

This research used Amihud's (2002) illiquidity ratio to capture the degree of illiquidity of each SEO-issuing firm. Amihud and Mendelson (1986), who are the first to have examined this relationship, found that there is a positive relationship between stock illiquidity and stock return. Amihud (2002) later proposed an illiquidity measure, which is one of the most widely used metrics in the current finance literature. Following Malkhozov et al. (2017), this research also took the natural log of the ratio to reduce the impact of outliers. The ratio is specified as follows:

$$\text{Illiquidity}_{i.t} = ln\left(1 + \frac{|R_{it}|}{Vol_{it}}\right) \tag{8}$$

where $|R_{it}|$ is the absolute value of the return for stock i at time t. Vol_{it} is the total dollar value trading volume of stock i at time t, for each stock during the event window. The total dollar trading volume is calculated as the number of shares traded on day for stock i at time t, multiplied by the stock price of stock i on each trading day during the event window.

Information Asymmetry

Following Shroff et al. (2013) and Chae (2005), this study used the bid–ask spread as a proxy for information asymmetry. A larger spread indicates a higher level of information asymmetry, which is typically observed in the days leading up to the announcement and is followed by a drop in the spread after the SEO announcement. The larger spread is typically observed in tighter liquidity conditions, which occurs when there is a disagreement between market markers (who set the ask price) and investors (who set the bid price) regarding the fair value of the stock. A larger disagreement is usually an indication of higher information asymmetry between the investor and market maker, resulting in a larger bid-ask spread (Gregoriou, Ioannidis & Skerratt 2005). The natural log was also applied to the bid–ask spread to minimise the impact of outliers in the data (Coller & Yohn 1997). The bid–ask spread is calculated as follows:

$$\text{Bid–Ask Spread}_{i,t} = ln(Ask\ price_{it}\ -\ Bid\ price_{it}) \tag{9}$$

Market-sensitive Announcements

If an announcement is market sensitive, firms are required to divulge this information to the ASX (2021e) as part of their continuous disclosure requirements. This variable was measured based on the number of market-sensitive disclosures released by each firm during the 6 months [−16 to −195 days] leading up the SEO announcement event window. Table 4.2 provides a summary of the number of market-sensitive announcements in the sample by SEO type. The Morningstar DatAnalysis Premium database[19] classifies each announcement type as either market sensitive or non-sensitive and was used to identify market-sensitive announcements in this research.

[19] https://datanalysis.morningstar.com.au/licensee/datpremium/html/ASX_Announcements_Onesheet.pdf

Table 4.2: Number of Market-sensitive Announcements

SEO Type	Number of Announcements
Private placement	3,118
Placement & share purchase plan	1,198
Placement & non-renounceable issue	840
Renounceable rights issue	753
Non-renounceable rights issue	634
Bonus issue	218
Placement & renounceable rights issue	217
Share purchase plan	83
Renounceable & non-renounceable rights issue	25

Corporate Insider Trading Behaviour

Corporate insider trading behaviour is an indicator variable that captures whether corporate insiders engaged in trading activity during the 31-day event period. If a firm makes a disclosure of trading activity via Appendix 3Y[20] or Form 604[21] submitted to the ASX, this variable takes the value of 1, and 0 otherwise. As part of an ASX-listed firm's continuous disclosure requirement, it is required to complete Appendix 3Y or Form 604 if there has been a *change in a director's interest* in the firm. This information is also made public to all existing and potential investors after it is reviewed by the ASX. If a corporate insider trades during the SEO event window, it is interpreted as a signal for shareholders to follow this behaviour since they assume that corporate insiders have superior knowledge about the firm. The increase in the trading activity by shareholders who mimic the trading behaviour of corporate insiders is expected to instigate abnormal return volatility, particularly if corporate insiders sell shares during the SEO event window.

[20] https://www.asx.com.au/documents/rules/Chapter03.pdf
[21] https://download.asic.gov.au/media/1263166/604.pdf

4.2.2.2.2.2 Firm-specific factors

Cost of Equity Capital

After the introduction of the capital asset pricing model, a debate has emerged in the finance literature regarding the measure that can most accurately determine a firm's cost of equity capital. Although the Reserve Bank of Australia suggests the use of the average realised returns and P/E ratios, they are all ex-post measures. Christensen, de la Rosa and Feltham (2010) performed an in-depth comparison of the appropriateness of ex-ante versus ex-post cost of equity capital. It was concluded that when firms raise capital, investors favour an ex-ante cost of equity capital as it provides them with more confidence over the future viability of the business, given that it uses future growth estimates as its basis. As such, for the case of SEOs, it is more appropriate to use an ex-ante measure to allow firms and their investors to understand the *expected* change in returns, and thus the expected volatility. To capture the future prospects of the firm, this research used Easton's (2004) measure of cost of equity capital. This proxy is a forward-looking measure that captures the future growth of the P/E ratio, which captures the cost of equity more accurately. The formula is specified as follows:

$$\text{Cost of Equity}_{i,t} = \sqrt{\frac{1}{(PEG)}} \tag{10}$$

where:

$$PEG = \frac{\left(\frac{P}{E_{it}}\right)}{(Annual\ EPS\ growth\ rate)}$$

where the $\left(\frac{P}{E_{it}}\right)$ is the price to earnings ratio of firm i for each day t during the event window and the annual EPS (earnings per share) growth rate is calculated as $\frac{EPS_{t-1} - EPS_t}{EPS_t}$.

Market-to-Book Value (MBV)

The *MBV* measures the degree to which a firm is overvalued during the SEO announcement event period. A firm that is overvalued is expected to produce higher returns, which manifests into higher levels of volatility. Following Sloan (1996), the natural log of the *MBV* was also taken to smoothen the data. The measure is specified as follows:

$$\text{Market-to-book value}_{i,t} = ln\left(\frac{Market\ Capitalisation_{it}}{Book\ Value_{it}}\right) \tag{11}$$

where the market capitalisation is calculated by multiplying the stock price by the total number of shares outstanding for firm i at time t. The book value is calculated by taking the book value (total assets – total liabilities) multiplied by the total number of shares outstanding for firm i at time t.

Firm Size

It is argued that larger firms experience lower volatility because of the lower (but more consistent) returns arising from the higher degree of stock liquidity (Banz 1981; Drew 2003; Reinganum 1981). However, when larger firms issue an SEO, the announcement is received more favourably than that of a smaller firm. This is because shareholders are more confident about the larger firm's future and therefore are more confident that they will eventually be adequately compensated through a reasonable return on their investment. This aspect is likely to attract more shareholders to compete for being part of the equity-raising process, resulting in elevated levels of return volatility. This research used market capitalisation to accurately capture the dynamic changes in business size (Dang, Li & Yang 2018). The natural log of market capitalisation was also taken to reduce the effect of outliers (Sloan 1996). The market capitalisation is calculated as follows:

$$\text{Market Capitalisation}_{i,t} = \ln(P_{it}\ x\ SO_{it}) \tag{12}$$

where P_{it} is the stock price of firm i at time t and SO_{it} is the total number of shares outstanding for firm i at time t.

4.2.2.2.2.3 Market factors

Economic Disruptions

Economic disruptions are classified as an indicator variable that captures the three economic disruption periods specified in this research: the early 2000s' dot-com bubble (Goodnight & Green 2010), the 2008 GFC (ASX 2010) and the COVID-19 pandemic (World Health Organization 2021). This variable takes the value of 1 during any of these disruption periods, and 0 otherwise.

Aggregate Market Volatility

Two proxies are widely used in the finance literature for volatility, namely, the standard deviation of returns (Du & Wei 2004; Goetzmann & Jorion 1999) and conditional variance estimated from Engle's (1982) GARCH model (Bakry 2006; Goyal 2000; Kambouroudis, McMillan & Tsakou 2016; Lamoureux & Lastrapes 1990; Molnár 2016). Most recent studies have preferred the GARCH model over standard deviation because it accounts for heteroscedasticity and leptokurtosis in stock returns (Mandelbrot 1963; Pagan 1996; Pagan & Schwert 1990). These stylised features are important to capture for they reflect the true behaviour of stocks returns. These studies have shown that the GARCH specification is a powerful method to capture stock return volatility in financial markets. Therefore, in this research, the GARCH (1,1) model was employed to calculate the daily stock return volatility (in the form of conditional variance) for the ASX 200 Index. The conditional variance was then scaled by multiplying it by 100 to match the scale of the other independent variables used in the model.

4.2.2.3 Model 2: Abnormal Return Volatility (Economic Disruption Periods)

In Model 2, the dummy variable for economic disruptions (*DIS*) is interacted with each independent variable to isolate the effect of each determinant on abnormal return volatility during economic disruption periods (Yips & Tsang 2007).

$$AVAR\text{–}GARCH_{i,t} = \beta_0 + \beta_1 AVOL_{i,t} + \beta_{1a} AVOL_{i,t} * DIS_{i,t} + \beta_2 DISC_{i,t} + \beta_{2a} DISC_{i,t} * DIS_{i,t} + \beta_3 ILLIQ_{i,t} + \beta_{3a} ILLIQ_{i,t} * DIS_{i,t} + \beta_4 BAS_{i,t} + \beta_{4a} BAS_{i,t} * DIS_{i,t} + \beta_5 MSA_i + \beta_{5a} MSA_i * DIS_{i,t} + \beta_6 CIT_i + \beta_{6a} CIT_i * DIS_{i,t} + \beta_7 COE_{i,t} + \beta_{7a} COE_{i,t} * DIS_{i,t} + \beta_8 MBV_{i,t} + \beta_{8a} MBV_{i,t} * DIS_{i,t} + \beta_9 SIZE_{i,t} + \beta_{9a} SIZE_{i,t} * DIS_{i,t} + \beta_{10} AMV_t + \beta_{10a} AMV_t * DIS_{i,t} + \varepsilon_{i,t} \quad (13)$$

where:

$AVOL_{it} * DIS_{i,t}$ = the interaction of the *DIS* dummy variable with the abnormal trading volume of firm i on day t of the event period [−15, +15].

$DISC_{it} * DIS_{i,t}$ = the interaction of the *DIS* dummy variable with the SEO discount of firm i on day t of the event period,

$ILLIQ_{it} * DIS_{i,t}$ = the interaction of the *DIS* dummy variable with the stock illiquidity of firm i on day t of the event period,

$BAS_{it} * DIS_{i,t}$ = the interaction of the *DIS* dummy variable with the bid–ask spread of i on day t of the event period,

$MSA_i * DIS_{i,t}$ = the interaction of the *DIS* dummy variable with the number of market-sensitive announcements released by firm i in the 6 months leading up to the event period,

$CIT_i * DIS_{i,t}$ = the interaction of the *DIS* dummy variable with the dummy variable that reflects whether corporate insiders engaged in trading activity during the 31-day event period.

$COE_{it} * DIS_{i,t}$ = the interaction of the *DIS* dummy variable with the cost of equity capital of firm i on day t of the event period,

$MBV_{it} * DIS_{i,t}$ = the interaction of the *DIS* dummy variable with the market-to-book value of firm i on day t of the event period,

$SIZE_{it} * DIS_{i,t}$ = the interaction of the *DIS* dummy variable with the firm size of firm i on day t of the event period,

$AMV_t * DIS_{i,t}$= the interaction of the *DIS* dummy variable with the aggregate market volatility of the ASX 200 Index on day t of the event period,

$\varepsilon_{i,t}$ = the error term.

4.3 Robustness Testing

This research applied several robustness tests to identify whether the findings are sensitive to adjustments in the methodology or the estimation process. First, both models were re-estimated under the cluster sandwich estimator, that is, 'vce(cluster ID)', where each panel ID refers to each 31-day event window. This robust standard error estimator accounts for the correlation of observations within each panel ID. Second, an alternate proxy for the dependant variable (*AVAR–GJR–GARCH*) was employed to confirm that the results of the base model measure (*AVAR–GARCH*) hold after applying this substitution. Last, the independent variables, which consistently produced the largest coefficients and were also statistically significant across most SEO types and sectors (*AVOL* and stock illiquidity), were replaced with alternate proxies to confirm that the results remain unchanged. These robustness tests were performed for the aggregate market, each SEO type and each Australian sector.

4.3.1 Ensuring Robust Standard Errors

Models 1 and 2 were originally estimated under the Huber–White robust estimates of the standard error specification, namely, 'vce(robust)'. This method assumes that the individual observations in each event period are independent. To ensure the robustness of the results, the models were re-estimated under an alternative specification, 'vce(cluster)', which relaxes the assumption of independence of the observation and thus allows clustering of the standard errors for each 31-day event window. This estimation technique accommodates and adjusts for the potential correlation of observations within each event period if it exists.

4.3.2 Employing an Alternative Proxy for Abnormal Return Volatility

Models 1 and 2 were also re-estimated using an alternative proxy for abnormal return volatility. In this case, *AVAR–GARCH* was replaced with *AVAR–GJR–GARCH* to confirm that the results remain robust. This proxy accommodates the leverage effect within the estimation process. Equation (5) in Section 4.2.2.2.1 provides a detailed explanation of the derivation of *AVAR–GJR–GARCH*.

4.3.3 Using Alternative Proxies for Independent Variables

Models 1 and 2 were again re-estimated using alternative proxies for variables that produced large coefficients, which were also statistically significant at 5%. Notably, the coefficient size and statistical significance for each SEO type and sector varied. Therefore, in this research, alternative proxies were employed for the variables (excluding dummy variables) in which the coefficients were consistently large and statistically significant across *most* SEO types and sectors. The variables that fitted these criteria were *AVOL* and illiquidity. The alternative proxies are described in Sections 4.3.3.1 and 4.3.3.2.

4.3.3.1 Abnormal Volume Turnover

Chae (2005) used an alternative proxy for abnormal trading volume, namely, 'abnormal turnover ratio[22] (*ATR*)'. This ratio is similar to the base model *AVOL* proxy, but also accounts for the number of shares outstanding to capture the daily turnover. It should be noted that when measuring $\tau_{i,t}$, the 'trading volume' is divided by the 'shares outstanding' to present the daily volume turnover on a *per share* basis. The ratio is specified as follows:

$$Abnormal\ Volume\ Turnover(\xi_{i,t}) = \tau_{i,t} - \bar{\tau}_{i,t} \tag{14}$$

$$\tau_{i,t} = \frac{Trading\ Volume_{i,t}}{Shares\ Outstanding_{i,t}}$$

$$\bar{\tau}_{i,t} = \frac{\sum_{t=-260}^{t=16} \tau_i}{245}$$

where:

$\tau_{i,t}$ is the daily turnover volume per share of firm i on day t of the 31-day event period,

$\bar{\tau}_{i,t}$ is the average turnover volume of firm i during the estimation period. This is calculated as the total turnover volume scaled by the number of days in the estimation period (i.e. 245 days).

4.3.3.2 Liquidity

Another widely used proxy for the liquidity of a firm is the Amivest liquidity ratio (*LIQ*) (Goyenko, Holden & Trzcinka 2009). The base model proxy (Amihud 2002) measures stock 'illiquidity', whereas the Amivest proxy measures stock liquidity. The coefficients are expected

[22] The abnormal turnover ratio was scaled by 1,000 to allow easier interpretation of the coefficient when comparing it with those for the dependant and other independent variables. Applying this scaling did not affect the statistical significance of the variable.

to remain statistically significant but would be inverted. For example, an RRR coefficient greater (less) than 1 for illiquidity is expected to be less (greater) than 1 for liquidity. This is because a higher degree of stock illiquidity equates to a lower degree of stock liquidity. The natural log of the Amivest liquidity ratio was also applied to this proxy to minimise the impact of outliers in the data (Goyenko, Holden & Trzcinka 2009). The Amivest liquidity ratio is specified as follows:

$$\text{Amivest liquidity ratio}_{i,t} = \frac{Vol_{i,t}}{ASR_{i,t}} \tag{17}$$

where:

Vol is the total value of volume traded, measured as the number of shares traded multiplied by the share price of firm i on day t of the 31-day event period.

ASR is the absolute stock return of firm i on day t of the 31-day event period.

4.4 Data Sources

This study utilised the daily closing stock prices of firms listed on the ASX-200 Index from January 1998 to December 2020. In addition to a broad coverage over the entire study period, particular attention was given to the three economic periods of disruption in Australia (characterised by periods of abnormal return volatility), namely, the dot-com bubble (1999–2001), the GFC (2008–2009) and the COVID-19 pandemic (January 2020–December 2020). Moreover, comparative analysis was undertaken between the abnormal return volatility during the entire sample period (Model 1) and economic disruption periods (Model 2). Although this research acknowledges that the COVID-19 pandemic is ongoing, for the purposes of allowing ample time between econometric modelling and the recording of results, the data collection concluded on 31 December 2020. The Global Industry Classification Standard (GICS)[23] was used to classify the appropriate sector that was attributed to each stock. Daily closing stock prices of each firm was obtained from the Refinitiv Eikon database, and announcement data for each SEO was obtained from the Morningstar DatAnalysis Premium database. A summary of all the data, and the data sources, are presented in Table 4.3.

To minimise the possibility of bias in the dataset, the following selection criteria were employed:

1. If a firm did not undertake an SEO during the study period, it was removed from the sample.
2. If a single SEO event consists of multiple related announcements released over multiple days, the event date used was the first announcement.
3. If there were instances where media outlets had released news or information about the SEO prior to the official SEO announcement on the ASX, the event date was brought forward to the date of the media release. The source of all news outlets is the Factiva database.[24]
4. If a firm released other market-sensitive announcements during the [−15, +15] event window, the SEO event was not included in the sample with the purpose of avoiding information contamination due to other simultaneous firm-related events. Examples of such announcements include the interim and annual report, a merger or acquisition, dividends, stock splits, market buybacks or delisting.

[23] Each of the 11 Australian sectors were categorised in accordance with the GICS framework, which is a globally followed industry classification framework. The GICS framework allocated each firm to a sector based on their core activities. The 11 GICS sectors are Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials, Information Technology, Materials, Communication Services, Real Estate and Utilities. The classifications can be found at https://www.marketindex.com.au/asx-sectors
[24] https://www.dowjones.com/professional/factiva/

5. If the firm announced an SEO after the end of the trading day or before the trading day opened (i.e. between 4 pm and 10 am), the announcement day was set as the following trading day (Lin, F & Gannon 2007).
6. If the SEO announcement included related information about an acquisition where market participants were learning of this acquisition for the first time, to avoid information contamination the announcement was not included in the sample.
7. If the SEO announcement occurred within the first 260 trading days of its listing date, it was not included in the sample as it would not satisfy the 245-day estimation window [−260 days to −16 days] requirement as the reference point.
8. If a firm operated as a group entity, SEOs announcements for their subsidiaries were removed from the sample due to their SEO offer prices not being reflected in the ASX-listed group stock price. It should be noted that SEOs announced by the group itself were retained in the sample.

After applying these selection criteria, 158 stocks remained in the sample, which represent approximately 80% of the ASX 200 index and therefore still adequately represents the index. These 158 stocks which were carried through to the econometric modelling performed in Phase 1 and Phase 2.

Table 4.3: Summary of Data Definitions and Sources

Variable Name	**Abbreviation**	**Variable Measurement**	**Empirical Specification**	**Source**
Abnormal Return Volatility (traditional measure)	*AVAR*	The average firm *i*'s squared abnormal returns during the event window *t*, divided by the variance of the market model returns of firm *i* during the estimation window [−260 days to −15 days]. An *AVAR* value between 0 and 1 indicates less-than-normal volatility is experienced, a value of 1 indicates a normal level of volatility is experienced, and a value above 1 indicates abnormal return volatility is experienced during the event window.	$AVAR_{i,t} = \frac{\mu_{i,t}^2}{\sigma_i^2}$	Refinitiv Eikon
Abnormal Return Volatility – GARCH	*AVAR–GARCH*	The average of the squared abnormal returns of firm *i* for the event window *t*, divided by the conditional variance of firm i's returns during the 245-day estimation window [–260 days to –15 days]. An *AVAR–GARCH* value between 0 and 1 indicates less-than-normal volatility is experienced, a value of 1 indicates a normal level of volatility is experienced, and a value above 1 indicates abnormal return volatility is experienced during the event window.	$AVAR\text{–}GARCH_{i,t} = \frac{\mu_{i,t}^2}{h_i}$ $where\ h_i = \alpha_{i,0} + \sum_{i=1}^{q} \alpha_i \varepsilon_{i,t-1}^2 + \sum_{i=1}^{p} \beta_j h_{i,t-1}^2$	Refinitiv Eikon
Abnormal Return Volatility – GJR–GARCH	*AVAR–GJR–GARCH*	The average of the squared abnormal returns of firm *i* for the event window *t*, divided by the conditional variance (which includes the leverage effect) of firm i's returns during the estimation window [–260 days to –15 days]. An *AVAR–GJR–GARCH* value between 0 and 1 indicates less-than-normal volatility is experienced, a value of 1 indicates a normal level of volatility is experienced, and a value above 1 indicates abnormal return volatility is experienced during the event window.	$AVAR\text{–}GJR\text{–}GARCH_{i,t} = \frac{\mu_{i,t}^2}{h_i}$ $where\ h_i = \alpha_0 + \sum_{i=1}^{q} (\alpha_1 \varepsilon_{t-i}^2 + \delta \varepsilon_{t-i}^2\, d_{t-i}) + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$	Refinitiv Eikon

Abnormal Trading Volume	*AVOL*	The daily trading volume of firm i on day t of the SEO event window, divided by the average trading volume of firm i during the 245-day estimation window [−260, −16]. An $AVOL_{i,t}$ value between 0 and 1 indicates a less-than-normal trading volume is experienced, a value of 1 indicates a normal level of trading volume is experienced and a value above 1 indicates abnormal trading volume during is experienced during the event window.	$AVOL_{i,t} = \frac{\overline{DTV_{it(event)}}}{\overline{ATV_{i(est)}}}$	Refinitiv Eikon
SEO Discount	*DISC*	The percentage difference between the SEO offer price and the end of day closing price for each day of the event window.	$DISC_{i,t} = \frac{P(SEO)_{i,t} - P(close)_{i,t-j}}{P(close)_{i,t-j}}$	Morningstar DatAnalysis
Stock Illiquidity	*ILLIQ*	The natural log of 1 plus the absolute value of the return for stock i at time t, divided by the total dollar value trading volume of stock i at time t, for each stock during the event window. The total dollar trading volume is calculated as the number of shares traded on day for stock i at time t, multiplied by the stock price of stock i on each trading day during the event window.	$ILLIQ_{i.t} = ln\left(1 + \frac{\lvert R_{it}\rvert}{Vol_{it}}\right)$	Refinitiv Eikon
Information Asymmetry (Bid–Ask Spread)	*BAS*	The natural log of the difference in the ask price and bid price for each firm during the event window.	$BAS_{i,t} = ln(Ask\ price_{it} - Bid\ price_{it})$	Refinitiv Eikon
Market-sensitive Announcements	*MSA*	Total of all market-sensitive announcements issued during the 6 months [−16 to −195 days] leading up to the SEO event window	Total of all market-sensitive announcements issued during the 6 months [−16 to −195 days] leading up to the SEO event window	Morningstar DatAnalysis
Corporate Insider Trading Behaviour	*CIT*	A dummy variable that captures whether corporate insiders undertook trading activity during the 31-day event period.	1 = a disclosure of corporate insider trading activity submitted via an Appendix 3Y form. 0 = no disclosure of corporate insider trading activity via an Appendix 3Y form.	Morningstar DatAnalysis

Cost of Equity Capital	*COE*	The square root of 1 divided by the PE growth (PEG). The PEG is calculated as the price to earnings ratio of firm i for each day t during the event window and the annual EPS (earnings per share) growth rate is calculated as $\frac{EPS_{t-1} - EPS_t}{EPS_t}$.	$COE_{i,t} = \sqrt{\frac{1}{(PEG)}}$ where $PEG = \frac{(\frac{P}{E_{it}})}{(Annual\ EPS\ growth\ rate)}$	Refinitiv Eikon
Market-to-Book Ratio	*MBV*	The market capitalisation (calculated as the stock price multiplied by the total number of shares outstanding for firm i at time t) divided by the book value (calculated as the total assets multiplied by the total number of shares outstanding for firm i at time t).	$MBV_{i,t} = ln\left(\frac{Market\ Capitalisation_{it}}{Book\ Value_{it}}\right)$	Refinitiv Eikon
Firm Size	*SIZE*	Firm size is represented by the market capitalisation. This is calculated as the stock price of firm i at time t multiplied by the total number of shares outstanding for firm i at time t.	$SIZE_{i,t} = \ln(P_{it}\ x\ SO_{it})$	Refinitiv Eikon
Economic Disruptions	*DIS*	A dummy variable that captures whether there was an economic disruption during the SEO event window. The three economic disruptions included are the dot-com bubble, the GFC and the COVID-19 pandemic.	1 = if an economic disruption occurred during the SEO event window. 0 = if an economic disruption did not occur during the SEO event window.	▪ Dot-com bubble: (Goodnight & Green 2010) ▪ GFC (ASX 2010) ▪ COVID-19 pandemic (World Health Organization 2021)
Aggregate Market Volatility	*AMV*	Market volatility for the ASX 200 Index returns based on a GARCH(1,1) estimation method.	$AMV_{i,t} = h_i = \alpha_{i,0} + \sum_{i=1}^{q} \alpha_i \varepsilon_{i,t-1}^2 + \sum_{i=1}^{p} \beta_j h_{i,t-1}^2$	Refinitiv Eikon

4.5 Pre- and Post-estimation Tests

4.5.1 Pre-estimation Testing

As part of preliminary testing, three main tests were undertaken: multicollinearity test using a pairwise correlation matrix, panel unit root testing and serial correlation testing. Panel unit root testing was undertaken to ensure that the variables are stationary across all panels in the sample. Since the dependant variable is categorical in nature, unit root testing was not required for this variable, but was still performed on the *AVAR–GARCH* and *AVAR–GJR–GARCH* continuous variables. The results of these preliminary tests are discussed in the next chapter in Section 5.2.3.

Unit Root Testing

In this research, a series of panel unit root tests were performed to ensure stationarity. These include the Levin, Lin and Chu (2002), Im, Pesaran and Shin (2003), augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) – Fisher type (Choi 2001) tests. The null hypothesis for these tests is as follows:

H_0: All panels contain unit roots.

H_1: All panels are stationary.

If the *p*-value of each test is less than 0.05 (5% significance level), the null hypothesis is rejected, and the panels are considered stationary.

Multicollinearity Testing

The variance inflation factor is commonly used to check data for multicollinearity. However, since this method is used for time series datasets, it would not be appropriate in this study's context. For panel datasets, a pairwise correlation matrix is commonly constructed to check for multicollinearity between the independent variables. The correlation matrix calculates the degree of correlation (represented as a correlation coefficient) between the dependant variable and each independent variable to test for the presence of multicollinearity. The literature has not prescribed a set correlation coefficient that can be considered the maximum correlation coefficient before multicollinearity is declared. The current research employed the commonly followed correlation coefficient of 0.80 for confirming multicollinearity (Brooks 2014). Generally, if multicollinearity is observed, one of the conflicting variables will be removed from the model. However, if all correlation coefficients are less than 0.80, no variables are required to be removed.

4.5.2 Post-estimation Testing

Serial Correlation Testing

Serial correlation testing is undertaken to confirm that there are no instances of autocorrelation in the error term, thus minimising the risk of endogeneity or omitted variable bias within the model. To check for autocorrelation, Wooldridge's (2002) test for serial correlation in panel data is used (Drukker 2003). The hypotheses for this test are as follows:

H_0: There is no first-order autocorrelation.

H_1: First-order autocorrelation is present in the panels.

If the *p*-value of the test is more than 0.05 (5% significance), the null hypothesis is not rejected, and thus, there is no serial correlation in the data.

4.6 Summary

This chapter explained the research methodology used to answer the research questions and objectives of this thesis. This includes an explanation and justification of the econometric models using MLR modelling, followed by a discussion of the robustness tests employed. Furthermore, it also provided an explanation of the measurement of the dependant and independent variables based on academic literature. Then, it described the data sources, the data collection methods and the selection criteria for the variables and the study period. The concluding section of this chapter provided an explanation of the various preliminary tests that were undertaken to ensure the stability and reliability of the data. The results of these preliminary tests along with the MLRs for Models 1 and 2 are provided in the next chapter.

Chapter 5: Preliminary and Aggregate Market Results

5.1 Introduction

This chapter provides a comprehensive discussion of the preliminary test results and the aggregate market results obtained from the models specified in Chapter 4. In this chapter, research question (RQ) 1 from Chapter 1 is addressed and is restated below:

RQ1: Is there a significant increase in abnormal return volatility across the aggregate market during periods of economic disruption compared with the entire sample period and what are its determinants?

In this chapter, section 5.2 first presents the descriptive statistics for the aggregate market and results of the preliminary tests, which include checks for multicollinearity, unit root and serial correlation. Second, sections 5.3 and 5.4 discuss the Phase 1 and 2 results for the aggregate market, which addresses Hypothesis 1 of this thesis. With respect to Phase 1, it compares the abnormal return volatility as measured by the traditional abnormal return volatility proxy (*AVAR*) and the improved GARCH-based proxies (*AVAR–GARCH* and *AVAR–GJR–GARCH*). Following this, the improved proxies are used in Phase 2 as part of MLR modelling to obtain the results for Model 1 and Model 2, which were specified in Chapter 4.

5.2 Preliminary Analysis

5.2.1 Descriptive Statistics

Table 5.1 (Panel A) summarises the descriptive statistics for the aggregate market for the entire sample period. A comparison of the three proxies for the dependant variable, abnormal return volatility, shows that the traditional measure (*AVAR*) has the highest mean of 1.15 and the highest standard deviation of 3.74. This result indicates that the traditional measure produces not only the highest abnormal return volatility values, but also the largest swings in response to SEO announcements. A comparison of these values with those for the improved proxies (see Figure 5.1) shows that *AVAR–GARCH* and *AVAR–GJR–GARCH* both produce a lower mean (0.69 and 0.70) and standard deviation (1.92 for both), indicating that these proxies experience less swings in their values. On adjusting for the stylised features of stock returns in *AVAR–GARCH* and *AVAR–GJR–GARCH*, it becomes apparent that the traditional *AVAR* proxy tends overstates the size of the abnormal return volatility experienced by firms.

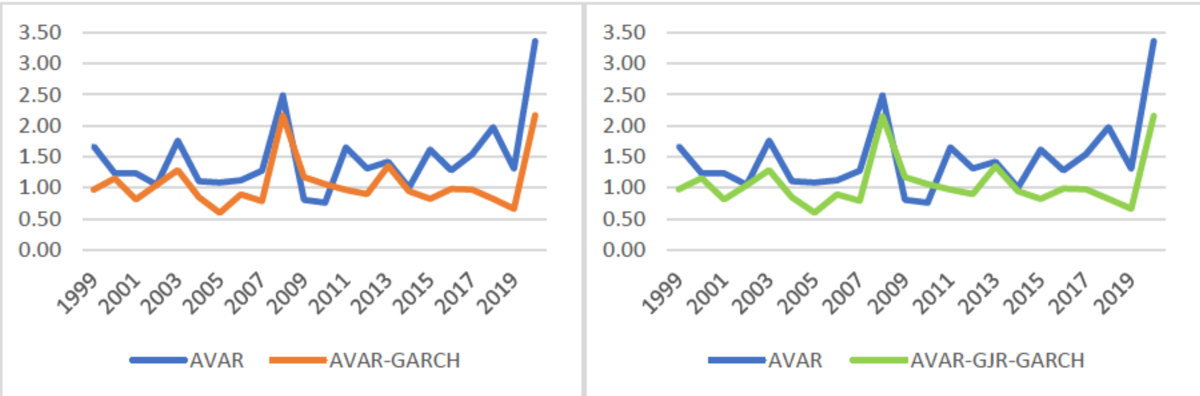


Figure 5.1: Comparing the *AVAR*, *AVAR–GARCH* and *AVAR–GJR–GARCH* Proxies

Note. Comparison of traditional abnormal return volatility proxy (*AVAR*) to the two improved proxies (*AVAR–GARCH* and *AVAR–GJR–GARCH*).

The large kurtosis values for the abnormal return volatility proxies (*AVAR*, *AVAR–GARCH* and *AVAR–GJR–GARCH*) across all SEO types suggest that the data distribution is heavy tailed. Although heavy-tailed distributions can be deemed higher risk, they are also an inherent feature of financial asset data (Brennan & Subrahmanyam 1996). Alberg, Shialit and Yousef (2008) asserted that heavy tails are a sign of volatility clustering and leptokurtosis (observations that are clustered together, resulting in the peak/kurtosis to be substantially higher than a normal distribution) and are also commonly observed in financial asset data. The heavy-tailed distributions are also evident in *AVOL*, *ILLIQ* and *COE*. The high kurtosis for *AVOL* is because it has a causal relationship with *AVAR*, and thus experiences a similar fat-tailed distribution (Shahzad et al. 2014). The large kurtosis for *ILLIQ* is likely due to large spikes in stock illiquidity occurring during economic disruptions resulting in a fatter tail distribution, relative to the low levels of stock illiquidity during normal economic periods (Fry 2018).

The abnormal return volatility proxies also exhibit a high positive skewness. The high skewness arises because most of the abnormal return volatility values are closer to 0, with spikes in these variables only occurring during the [−1, +3] period of the entire 31-day SEO event window (see Figure 5.2). Further, *AVOL* behaves similarly and presents high skewness. The MLR employed in this thesis does not require normally distributed data, and thus, these variables can still be used in the regression despite having high skewness and kurtosis values. However, for the purpose of completeness, they are still discussed in the descriptive statistics.

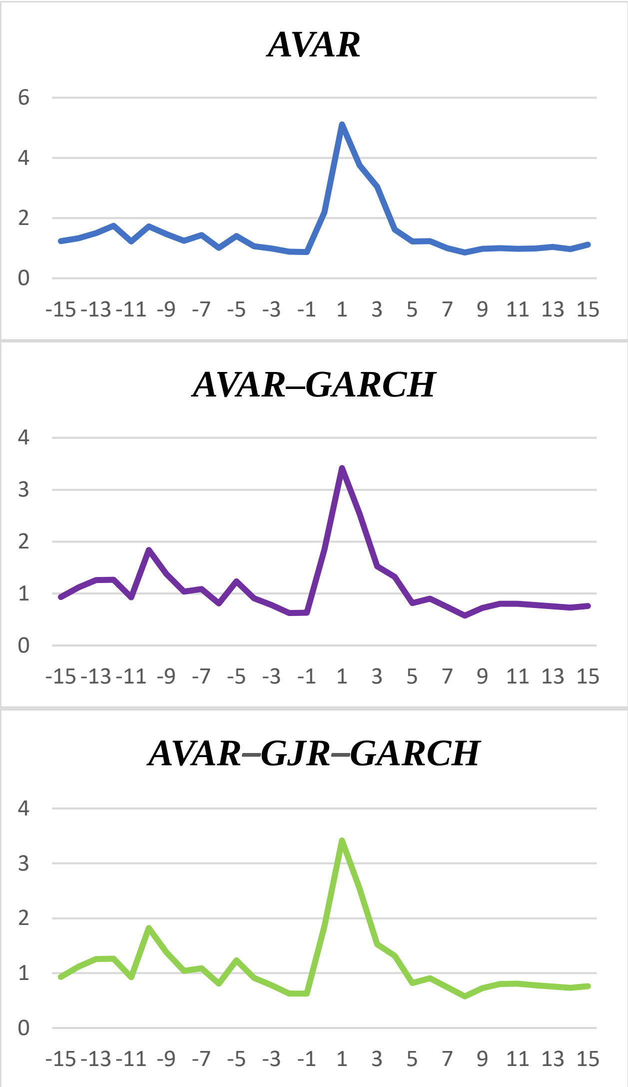


Figure 5.2: Average Daily Abnormal Return Volatility during the SEO Event Window

Moreover, the comparison in Table 5.1 between non-economic disruption periods (Panel B) and economic disruption periods (Panel C) highlights notable differences between these periods. Overall, the descriptive statistics for a majority of the variables intensified during economic disruption periods. However, the mean values for *ILLIQ*, *DISC*, *MSA* and *MBV* were lower during economic disruptions. The fact that there is variation in the descriptive statistics for each variable justifies the importance of exploring the impact of SEO-induced abnormal return volatility not only for the entire sample period but also specifically during economic disruptions.

The *AVOL* of 1.49 indicates that firms, on average, experienced a 149% increase in abnormal trading volume during SEO announcements. The high standard deviation of 2.52 shows that the abnormal trading volume can experience fluctuations up to 2.52 times higher than the mean abnormal trading volume (1.49). The maximum *AVOL* of 99.79 indicates that the abnormal trading volume can experience extremely high values, which are likely to occur during economic disruptions. The SEO discount (*DISC*) mean value of 0.36 indicates that, on average, firms provided a 0.36% discount on additional shares issued to existing shareholders during SEOs. It should be noted that the maximum value of 100% is due to bonus issues whereby firms issued additional shares to existing shareholders at no cost. Another notable statistic is the mean firm size (*SIZE*) of 20.87, which is closer to the maximum value, indicating that most of the firms in this sample are larger in size. This is expected since this study covers the ASX 200 Index (200 largest firms by market capitalisation). The mean value for the bid–ask spread (−3.25) is negative because the natural logarithm was taken for this variable. A negative natural logarithm value indicates that the average bid–ask spread was between 0 and 1, which is common for ASX 200 stocks (Fabre & Frino 2004). All the remaining variables (*ILLIQ*, *COE*, *MBV* and *AMV*) have a low mean and standard deviation, which implies that firms across the ASX 200 Index have similar values. This is because the firms in this index are similar in size (relative to small capitalisation stocks, that is, ASX Small Ordinaries) and are likely to present similar values. Last, corporate insider trading behaviour (*CIT*), and economic disruptions (*DIS*) are both dummy variables and carry a value of 0 or 1.

Table 5.1: Descriptive Statistics (Aggregate Market)

Variable	Mean	Std. Dev.	Skewness	Kurtosis	Min	Max	Obs.
Panel A: Entire Sample Period							
AVAR	1.15	3.74	15.82	393.49	0.00	146.78	17,825
AVAR–GARCH	0.69	1.92	10.09	162.55	0.00	48.45	17,825
AVAR–GJR–GARCH	0.70	1.92	10.06	161.79	0.00	48.74	17,825
AVOL	1.49	2.52	16.25	441.4	0.00	99.79	17,825
DISC	0.36	1.41	5.70	39.97	−0.54	100.00	17,825
ILLIQ	0.08	0.38	9.52	128.34	0.00	9.07	17,822
BAS	−3.25	1.46	0.43	3.70	−13.12	3.40	17,825
MSA	10.13	7.31	1.66	6.50	0.00	49.00	17,825
CIT	0.03	0.16	6.12	38.44	0.00	1.00	17,825
COE	0.26	0.13	6.82	110.4	0.00	2.62	17,825
MBV	0.83	1.00	0.54	4.43	−3.37	5.18	17,825
SIZE	20.77	1.87	−0.58	3.66	13.85	25.68	17,825
DIS	0.11	0.31	2.48	7.16	0.00	1.00	17,825
AMV	0.76	0.77	2.99	20.28	0.00	11.22	17,825
Panel B: Non-Economic Disruption Periods							
Variable	**Mean**	**Std. Dev.**	**Skewness**	**Kurtosis**	**Min**	**Max**	**Obs.**
AVAR	1.08	3.63	16.85	447.01	0.00	146.78	15,852
AVAR–GARCH	0.66	1.89	10.26	168.25	0.00	48.44	15,852
AVAR–GJR–GARCH	0.66	1.89	10.23	167.26	0.00	48.74	15,852
AVOL	1.47	2.53	16.94	472.06	0.00	99.79	15,852
DISC	0.42	1.43	5.53	37.49	0.00	16.14	15,852
ILLIQ	8.15	38.77	9.54	127.22	0.00	906.47	15,852
BAS	−3.37	1.40	0.40	3.92	−13.12	3.25	15,852
MSA	10.41	7.40	1.69	6.53	0.00	49.00	15,852
CIT	0.02	0.15	6.32	40.98	0.00	1.00	15,852
COE	25.29	12.94	7.29	117.78	0.30	262.22	15,852
MBV	0.85	1.01	0.54	4.52	−3.37	5.18	15,852
SIZE	20.87	1.85	−0.56	3.75	13.85	25.68	15,852
AMV	0.68	0.60	1.75	7.60	0.00	4.85	15,852
Panel C: Economic Disruption Periods							
Variable	**Mean**	**Std. Dev.**	**Skewness**	**Kurtosis**	**Min**	**Max**	**Obs.**
AVAR	1.64	4.49	10.89	174.96	0.00	90.30	1,973
AVAR–GARCH	0.94	2.16	9.04	130.37	0.00	40.91	1,973
AVAR–GJR–GARCH	0.94	2.16	9.06	130.60	0.00	40.88	1,973
AVOL	1.66	2.42	10.05	153.54	0.00	50.23	1,973
DISC	0.27	0.75	5.99	41.60	0.00	6.66	1,973
ILLIQ	6.56	28.81	7.48	80.69	0.00	470.74	1,973
BAS	−2.34	1.60	0.22	2.58	−5.46	3.40	1,973
MSA	7.94	6.10	1.14	3.67	0.00	27.00	1,973
CIT	0.04	0.19	4.94	25.44	0.00	1.00	1,973
COE	25.63	11.61	1.49	12.32	0.32	89.25	1,973
MBV	0.65	0.90	0.36	2.92	−1.47	3.29	1,973
SIZE	21.71	1.83	−1.07	4.11	16.41	24.82	1,973
AMV	1.44	1.41	2.04	9.25	0.01	11.22	1,973

Note. *ILLIQ*, *BAS*, *MBV* and *SIZE* are expressed in their natural logarithmic form to reduce the impact of outliers. Please refer to Table 4.3 in Chapter 4 for a summary of how each variable is measured and the empirical specifications.

5.2.2 Correlation Matrix

Table 5.2 shows the correlation between the dependant variable, *AVAR–GARCH*, and the various independent variables. *AVAR* and *AVAR–GJR–GARCH* have also been included in the correlation matrix, but *AVAR* is not used in the regression. Therefore, the high correlation to *AVAR* and *AVAR–GJR–GARCH* can be disregarded. With respect to the *AVAR–GJR–GARCH* variable, it substitutes *AVAR–GARCH* as the dependant variable as part of robustness testing, and therefore, the high correlation between *AVAR* and *AVAR–GARCH* can be disregarded. On observing all the other variables, the strongest positive correlation ($\rho = 0.44$) was identified between *BAS* (proxying for information asymmetry) and *SIZE*. This is an interesting result because larger firms are expected to have a lower degree of information asymmetry. However, it appears that during SEO announcements, information asymmetry tends to become more pronounced for larger firms. This result lends support to the adverse selection theory, which posits that larger firms tend to issue equity during periods of high information asymmetry to maximise capital-raising prospects (Myers & Majluf 1984). The second most notable positive correlation ($\rho = 0.31$) was between *DIS* and *AMV*. This is an expected result because the volatility of individual firms tends to be affected by aggregate market volatility, which can be intensified during economic disruptions (Campbell et al. 2001; Sharma, Narayan & Zheng 2014).

Other notable positive correlations include a 0.22 correlation between *DIS* and the *BAS*, a 0.21 correlation between *ILLIQ* and *AVAR–GARCH* and a 0.20 correlation between *AVOL* and *AVAR–GARCH*. The sizeable correlations between *ILLIQ* and *AVOL* highlight that they are likely to play a significant role in affecting the size of abnormal return volatility. The positive correlation between *DIS* and the *BAS* is expected because information asymmetry does tend to increase during periods of economic uncertainty. This is because firms are less concerned about improving disclosure during these times, and more concerned about keeping the business operational. The positive correlation between *ILLIQ* and *AVAR–GARCH* is also expected because when there is a higher degree of stock illiquidity, larger stock price swings tend to occur, which increases the likelihood of abnormal return volatility to occur (Amihud & Mendelson 1986; Asem, Chung & Tian 2016; Brennan & Subrahmanyam 1996; Datar, Naik & Radcliffe 1998; Hasbrouck 1993; Ho et al. 2005). The positive correlation between *AVOL* and *AVAR–GARCH* is also expected because there is a causal relationship between these two variables, whereby an increase in abnormal trading volume tends to cause an increase in abnormal return volatility (Shahzad et al. 2014).

There were also some notable negative correlations between some of the variables. The two correlations of interest are the correlation coefficient between *SIZE* and *ILLIQ* ($\rho = -0.38$) and the correlation coefficient between the *MBV* and the *COE* ($\rho = -0.28$). The negative correlation between firm size and stock illiquidity is expected because as firm size increases, the market capitalisation increases because of a rise in the number of shareholders, which boosts trading volume and decreases stock illiquidity. The negative correlation between the *MBV* and *COE* is also expected because if the stock price of a firm increases, investor sentiment improves, which means that firms can theoretically pay a lower rate of return to their investors. This can also be due to investors developing a 'fear of missing out' on the investment opportunity to earn higher returns. With respect to multicollinearity concerns, Brooks (2014) stated that if the correlation coefficients are less than 0.75, there is a low risk of multicollinearity within the model. Since all the correlation coefficients were less than 0.75, multicollinearity was not a concern, and thus, no adjustments were required to the specifications of the econometric model.

Table 5.2: Correlation Matrix

Variables	***AVAR***	***AVAR–GARCH***	***AVAR–GJR–GARCH***	***AVOL***	***DISC***	***ILLIQ***	***BAS***	***MSA***	***CIT***	***COE***	***MBV***	***SIZE***	***DIS***	***AMV***
AVAR	1.00													
AVAR–GARCH	0.73	1.00												
AVAR–GJR–GARCH	0.73	0.99	1.00											
AVOL	0.18	0.20	0.20	1.00										
DISC	−0.01	0.06	0.06	0.06	1.00									
ILLIQ	0.03	0.21	0.21	−0.05	0.11	1.00								
BAS	0.04	−0.04	−0.04	−0.02	0.05	−0.15	1.00							
MSA	−0.04	0.01	0.01	−0.02	0.06	−0.02	−0.19	1.00						
CIT	0.02	0.02	0.02	0.05	0.01	−0.02	0.03	−0.03	1.00					
COE	−0.01	0.03	0.02	0.08	0.20	0.13	−0.03	−0.01	0.00	1.00				
MBV	−0.01	0.02	0.02	−0.01	−0.03	−0.05	0.10	0.04	−0.03	−0.28	1.00			
SIZE	0.07	−0.09	−0.09	−0.02	0.01	−0.38	0.44	0.03	0.05	−0.07	−0.04	1.00		
DIS	0.05	0.04	0.04	0.02	−0.04	−0.01	0.22	−0.11	0.03	−0.01	−0.06	0.16	1.00	
AMV	0.04	0.05	0.04	0.03	0.00	−0.02	0.13	−0.03	0.05	0.03	−0.07	0.10	0.31	1.00

Note. *AVAR* is the traditional abnormal return volatility proxy and is calculated as the average of the squared abnormal returns for the event window divided by the variance of returns during the estimation window; *AVAR–GARCH* and *AVAR–GJR–GARCH* are the improved abnormal return volatility proxies, measured as the average of the squared abnormal returns for the event window divided by the conditional forecasted variance during the estimation window. The calculation of the conditional variance in the *AVAR–GJR–GARCH* proxy also accounts for the leverage effect within the conditional variance component; *AVOL* is the abnormal trading volume, calculated as the daily trading volume during the SEO event window divided by the average trading volume during the estimation window; *DISC* refers to the SEO discount, which is calculated as the difference between the SEO offer price and the closing share price, divided by the closing share price; *ILLIQ* is the stock illiquidity, which is the natural logarithm of 1 plus the absolute value returns divided by trading volume (in dollars); *BAS* is the bid–ask spread, which is calculated as the natural log of the difference between the ask price and the bid price; *MSA* refers to the number of market-sensitive announcements disclosed; *CIT* refers to corporate insider trading, which is a dummy variable that takes the value of 1 if corporate insiders engage in trading behaviour during the event window, and 0 otherwise; *COE* is the cost of equity capital, which is calculated as the square root of 1 divided by the PE growth ratio; *MBV* indicates the market-to-book value and is measured as the natural logarithm of the firm's market capitalisation divided by the book value; *SIZE* refers to the firm size, which is calculated as the natural logarithm of the share price multiplied by the number of shares outstanding; *DIS* is a dummy variable that that takes the value of 1 if there is an economic disruption period, and 0 otherwise; and *AMV* refers to the aggregate market volatility, which is calculated as the daily conditional variance (using GARCH (1,1) estimations) of the ASX 200 Index.

5.2.3 Unit Root Test Results

Table 5.3 reports the results of the unit root tests undertaken for each of the variables, which confirmed the stationarity of the variables. It should also be noted that the economic disruption (*DIS*) and corporate insider trading activity (*CIT*) variables were not subject to unit root testing since they are dummy variables. Moreover, unit root testing for *AVAR* was not undertaken because it was not used as a variable in the regressions owing to its limitations as an abnormal return volatility measure. Instead, *AVAR–GARCH* and *AVAR–GJR–GARCH* were used as the abnormal return volatility proxies and were included in the unit root tests.

A series of panel units root tests were undertaken to test for the stationarity of the data. The null hypothesis for the first test is that there is a 'common unit root process' (Levin, Lin & Chu 2002). The second series of tests have a null hypothesis that assumes an 'individual unit root process'. These tests include the Im, Pesaran and Shin (2003), the ADF–Fisher (Maddala & Wu 1999) and the PP–Fisher (Maddala & Wu 1999) tests. The results show that each variable across all unit root tests is statistically significant at 1%; thus, the null hypothesis is rejected, which confirmed that all the variables are stationary. All variables were first tested under an intercept specification at levels. All variables were found to be stationary under the intercept specification except for *MSA* and *SIZE*. These two variables were then tested under an intercept and trend specification at levels, which was found to be stationary. There is consistency in the unit root test results in which all tests confirmed that all variables are stationary in levels; that is, integrated order 0, that is, I(0).

Table 5.3: Unit Root Test Results

		Level				
Variable	**Specification**	**Null Hypothesis: Common Unit Root Process**	**Null Hypothesis: Individual Unit Root Process**			
		Levin, Lin & Chu *t*-stat	Im, Pesaran & Shin W-stat	ADF–Fisher Chi-square	PP–Fisher Chi-square	Decision
AVAR–GARCH	Intercept	−98.82***	−91.52***	9236.50***	10655.69***	I(0)
AVAR–GJR–GARCH	Intercept	−98.82***	−91.52***	9236.50***	10655.69***	I(0)
AVOL	Intercept	−89.27***	−63.63***	5952.19***	6723.26***	I(0)
DISC	Intercept	−6.48****	−4.35***	1348.89***	1340.27***	I(0)
ILLIQ	Intercept	−69.83***	−72.25***	7322.08***	9574.41***	I(0)
BAS	Intercept	−72.29***	−72.62***	7213.34***	8270.14***	I(0)
MSA	Intercept with trend	−119.28***	−92.39***	8286.60***	8284.21***	I(0)
COE	Intercept	−6.07***	−3.70***	1134.59***	1119.48***	I(0)
MBV	Intercept	−6.69***	−4.14***	1316.75***	1311.98***	I(0)
SIZE	Intercept with trend	−4.04***	−7.80***	1490.30***	1287.60***	I(0)
AMV	Intercept	−66.54***	−67.99***	6831.00***	8103.88***	I(0)

Note. *** indicates that the test statistic is statistically significant at 1%.

5.3 Phase 1 Results: Measurement and Comparison of Abnormal Return Volatility Proxies (Aggregate Market)

This section discusses the results of the measurement and comparison of abnormal return volatility for each of the three proxies. These results address Hypothesis 1, RQ1 and objective 1 of this thesis, which determine whether there is a difference in abnormal return volatility across the entire sample period relative to economic disruptions.

Table 5.4 presents the results of the abnormal return volatility for SEOs in the aggregate market for the entire sample period. The results show that abnormal return volatility persisted in almost all years. The only exceptions were the two years following the GFC (2009 and 2010) for which the *AVAR* measure was less than 1, indicating that firms experienced less-than-normal volatility in these years. A closer examination of the *AVAR* values reveals that they remained consistently above 1 during the peaks of economic disruptions (i.e. the dot-com bubble in the early 2000s, the 2008 GFC and the 2020 COVID-19 pandemic), lending support to Hypothesis 1. The fact that the *AVAR* was higher during economic disruptions warrants further investigation of how it manifested across each SEO type and each sector. This is covered in detail in Chapters 6 and 7, respectively. Of the three disruption periods, the largest *AVAR* was identified during the COVID-19 pandemic (3.36). The fact that the *AVAR* during the COVID-19 pandemic was almost three times the size of that during the dot-com bubble and almost 1.5 times higher than that of the GFC highlights that shareholders are more sensitive to SEO announcements during public health crises than during financial crises. Z Li et al. (2021) asserted that investors have a larger reaction (and possibly an overreaction) to firm announcements during public health crises because of the uncertainty surrounding the duration of the health crisis. This is because health crises have a more widespread effect on the economy than a financially induced crisis does, which is shorter in duration and is localised to specific sectors.

On comparing the improved *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies with the traditional *AVAR* measure, a notable difference can be observed in the size of the values (see Figure 5.1). As discussed earlier in Chapter 4, the limitation of the traditional *AVAR* measure is that it does not accurately capture volatility clustering, which is a vital stylised feature observed in financial stock return volatility (Tsay 1987). The *AVAR–GARCH* proxy solves this problem by using conditional variance, which uses previous period variance to determine the current period variance, that is, volatility clustering, thereby improving its accuracy (Alberg, Shalit & Yosef 2008; Bollerslev 1986). Moreover, the *AVAR–GJR–GARCH* proxy provides additional improvements by incorporating the leverage effect within the measurement of abnormal return volatility (Engle & Ng 1993; Glosten, Jagannathan & Runkle 1993; Nelson 1991; Yu 2005)

Table 5.4 shows that after accounting for the stylised features of stock return volatility, the improved proxies present lower coefficients in most of the years. This result indicates that the traditional *AVAR* proxy tends to overstate the impact of SEO announcements on abnormal return volatility. An interesting finding is that for 2002 and 2013, *AVAR* values that were greater than 1 are estimated to be less than 1 with the improved *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies. This is an important finding because it was assumed that abnormal return volatility was persistent across every year during normal economic periods, but just increased in intensity during economic disruption years. However, this result indicates that instead, firms in the aggregate market experienced less-than-normal volatility during normal economic periods and experienced abnormal return volatility only during economic disruptions.

Another key finding is that *AVAR* presented coefficients of less than 1 (0.81 and 0.76, respectively) for 2009 and 2010, although the improved proxies displayed them as higher than

1 (1.17 and 1.06, respectively). These results show that in circumstances where the *AVAR* is lower than 1, it understates the true extent of abnormal return volatility. This finding reinforces the importance of using the improved proxies to measure abnormal return volatility more accurately. As previously mentioned, Tsay (1987) asserted that by using conditional variance (where the prior period volatility is used to determine the current period volatility) as opposed to the standard variance measure, the accuracy of the abnormal return volatility measure improves. This effectively means that if the previous period volatility is high (low), the current period volatility will also be high (low). In the context of these findings, the abnormal return volatility was higher in the improved proxies during 2009. According to the 'volatility clustering' assumption of the GARCH specification, the abnormal return volatility should be higher in 2009 because the volatility in the prior year was also high, which was the year of the GFC. The results provide support to the theoretical contribution of this thesis that *AVAR–GARCH* and *AVAR–GJR–GARCH* are more accurate proxies for abnormal return volatility.

Table 5.4: Abnormal Return Volatility (*AVAR*, *AVAR–GARCH* and *AVAR–GJR–GARCH*) for Aggregate Market

Economic Disruption	Year	*AVAR*	*AVAR–GARCH*	*AVAR–GJR–GARCH*
	1999	1.67	0.97	0.97
Dot-com bubble	2000	1.23	1.15	1.16
	2001	1.23	0.81	0.81
	2002	1.05	1.05	1.05
	2003	1.76	1.28	1.29
	2004	1.10	0.85	0.85
	2005	1.09	0.60	0.60
	2006	1.12	0.89	0.90
	2007	1.27	0.79	0.79
GFC	2008	2.48	2.16	2.15
	2009	0.81	1.17	1.17
	2010	0.76	1.06	1.06
	2011	1.65	0.97	0.97
	2012	1.31	0.90	0.90
	2013	1.42	1.35	1.35
	2014	1.00	0.95	0.95
	2015	1.62	0.82	0.82
	2016	1.28	0.98	0.99
	2017	1.54	0.97	0.98
	2018	1.98	0.82	0.82
	2019	1.30	0.66	0.66
COVID-19 pandemic	2020	3.36	2.16	2.16

Note. This table presents the average *AVAR, AVAR–GARCH* and *AVAR–GJR–GARCH* values for produced the aggregate market (i.e. all SEO types) to represent the market-wide changes during the entire sample period. A value below 1 indicates that firms experienced less-than-normal volatility during SEO announcements. A value of 1 indicates that the SEO event had no impact the on the return volatility of firms. A value above 1 indicates that firms experienced a larger-than-normal (abnormal) impact on return volatility. As an example, a value of 2 indicates that firms experienced double the normal volatility, and a value of 0.50 indicates that firms experienced half the normal levels of volatility.

5.4 Phase 2 Results: Determinants of Abnormal Return Volatility (Aggregate Market)

This section provides the results of the MLRs for Phase 2, which examine the determinants of abnormal return volatility across the aggregate market. These results also address Hypothesis 1, RQ1 and objective number 1 of this thesis, which determine whether there is a difference in abnormal return volatility across the entire sample period relative to economic disruptions.

The results within this thesis present RRR coefficients rather than the regression coefficients. This is because when multinomial regressions are undertaken in academic literature, RRR coefficients allow the relationship between the dependant and independent variables to be more easily interpreted (Bruin 2006). The RRR describes the relative risk of falling into a treatment category rather than the base category. The actual regression coefficients themselves have not been included in the thesis for brevity purposes. However, the detailed results with the original coefficients can be supplied on request. Further, the statistical significance of both the regression and RRR coefficients are the same.

An RRR coefficient less than 1 indicates that for every 1 unit increase in the independent variable, a firm is more likely to experience *less-than-normal* return volatility (i.e. base category or category 0). In contrast, an RRR coefficient greater than 1 indicates that for every 1 unit increase in the independent variable, a firm is more likely to experience *abnormal* return volatility (i.e. the treatment categories). As described in Table 4.1 in Chapter 4, the dependant variable (*AVAR–GARCH*) is categorical with three treatment categories (1, 2 and 3), which represents a firm's relative risk of experiencing low, moderate and high levels of abnormal return volatility, respectively. In addition, two sets of models were estimated. Model 1 was used to examine the extent to which a set of SEO-specific, firm-specific and market-wide factors affect abnormal return volatility for the aggregate market across the entire sample period. Model 2, however, was used to examine the extent to which these same determinants affect abnormal return volatility during economic disruptions for the aggregate market. The results for both models are discussed in Sections 5.4.1 and 5.4.2.

5.4.1 Entire Sample Period (Model 1)

Table 5.5 displays the results of the aggregate market model (Model 1), which shows the RRR for each independent variable and their likelihood to instigate abnormal return volatility. The results show that abnormal trading volume (*AVOL*), the SEO discount (*DISC*), corporate insider trading (*CIT*), market-to-book value (*MBV*), economic disruptions (*DIS*) and aggregate market volatility (*AMV*) produced statistically significant RRR coefficients that were greater than 1. This indicates that for every 1 unit increase in each of these variables, firms experienced abnormal levels of return volatility. Although all variables had an effect, *AVOL* produced the highest coefficient in category 3 (1.33), indicating that for every 1 unit increase in *AVOL*, firms were 1.33 times more likely to experience *high* levels of abnormal return volatility during SEO announcements, than they were to experience 'less-than-normal' volatility (base outcome).

The independent variables *DISC* (1.09), *CIT* (1.59), *MBV* (1.20) and *AMV* (1.32) also contributed to abnormal return volatility, with the highest coefficients observed in category 2, highlighting that they elicited *moderate* levels of abnormal return volatility. The *DISC* coefficient of 1.09 means that for every 1% increase in the SEO discount, firms are 1.09 times more likely to experience moderate levels of abnormal return volatility. The positive relationship identified between a firm's discount and return volatility is consistent with K Chan and Chan (2014), who asserted that a larger SEO discount will increase a firm's return volatility caused by the large uptake of shares at lower prices than the current price.

With respect to *CIT*, the coefficient indicates that when corporate insiders engage in trading during the SEO announcement period, firms are 1.59 times more likely to experience moderate levels of abnormal return volatility. This result is consistent with that of many strands of research that argue corporate insiders reduce their stock holdings just before an SEO announcement, by exercising stock options (Cline et al. 2014; Del Brio, Miguel & Perote 2002; Hauser, Kraizberg & Dahan 2003). When corporate insiders disclose this behaviour to the ASX (via an Appendix 3Y submission), shareholders react negatively to this disclosure, which manifests as volatility (Hotson, Kaur & Singh 2007).

The *MBV* coefficient highlights that for every 1% increase in the market-to-book value, firms are 1.20 times more likely to experience moderate levels of abnormal return volatility. These findings are consistent with that of Ali, Hwang and Trombley (2003), who argued that there is a positive relationship between a firm's market-to-book value and return volatility. Moreover, they highlighted that the return volatility increases for larger firms, which is in line with the sample (ASX 200 firms) chosen in this thesis. Luo, Li and Liu (2021) suggested that the increased volatility during higher market-to-book value periods reflects positive market sentiment, which results in greater participation in SEOs, translating into higher levels of volatility. The coefficient for *AMV* shows that for every 1 unit increase in aggregate market volatility, firms are 1.32 more likely to experience moderate levels of abnormal return volatility. This result indicates that aggregate market volatility does affect the abnormal return volatility of individual firms. This finding is in line with those of previous research, which suggest that there is a positive relationship between the volatility of individual firms and the volatility of the market (Campbell et al. 2001; Rahman 2009; Smith & Yamagata 2011).

Last, economic disruptions (*DIS*) is a dummy variable, which also experienced abnormal return volatility, but with the highest coefficient of 2.05 observed in category 1. This result indicates that firms were 2.05 times more likely to experience *low* levels of abnormal return volatility during economic disruptions, compared with stable economic periods. Schwert (1990) asserted that a firm's return volatility is significantly higher during an economic crisis than it is in economic expansions owing to the higher levels of economic uncertainty. Given that the results show that firms experienced abnormal return volatility during economic disruptions (although low), it will be beneficial to understand the extent to which the regressors intensified the effect of this abnormal return volatility during these economic disruptions. Therefore, the economic disruptions dummy variable is interacted with each regressor, which is covered in the following subsection under the Model 2 results.

BAS (0.96) and *SIZE* (0.90) both produced RRR coefficients of less than 1. This result means that for every 1 unit increase in the bid–ask spread and firm size, firms were only 0.96 times and 0.90 times likely to experience abnormal return volatility, respectively. This is equivalent to stating that when the bid–ask spread and firm size increases, firms are more likely to experience less-than-normal volatility. This is an important finding because this thesis aims to not only highlight the factors that firms should be conscious of when issuing SEOs, but also the factors that firms can exploit without negatively affecting their shareholders. The fact that the RRR coefficient for the bid–ask spread (a proxy for information asymmetry) is less than 1, is surprising because investors typically dislike information asymmetry, which leads to a negative response and therefore an increase in return volatility (Chan, K & Chan 2014; West, KD 1988). However, the low coefficient highlights that firms do not need to be concerned about information asymmetry when issuing SEOs (usually experienced during high-growth periods). In contrast, the low coefficient for firm size is as expected, since it confirms that larger firms are less likely to experience abnormal return volatility. This result is in line with that of Perez-Quiros and Timmermann (2000), who showed that as firm size increases, return volatility decreases because of the higher degree of stock liquidity.

Last, illiquidity (*ILLIQ*), market-sensitive announcements (*MSA*) and cost of equity capital (*COE*) all produced coefficients close to 1, indicating that a 1 unit increase in these variables, had no effect on return volatility. This shows that investors appeared to disregard any market-sensitive announcements issued by firms, any changes in their stock illiquidity and cost of equity capital during SEOs.

Table 5.5: Model 1 – Regression Results for Aggregate Market (Entire Sample Period)

	AVAR–GARCH **Category**		
Category	**1**	**2**	**3**
Variable	RRR	RRR	RRR
AVOL	1.23***	1.30***	1.32***
	(0.03)	(0.05)	(0.05)
DISC	1.07***	1.09***	1.06
	(0.02)	(0.03)	(0.06)
ILLIQ	1.01***	1.01***	1.02***
	(0.00)	(0.00)	(0.00)
BAS	0.95**	0.99	0.92
	(0.02)	(0.03)	(0.05)
MSA	1.01***	1.02***	1.01
	(0.00)	(0.01)	(0.01)
CIT	1.49***	1.51*	1.05
	(0.20)	(0.37)	(0.42)
COE	0.99***	0.98***	1.00
	(0.00)	(0.00)	(0.00)
MBV	1.10***	1.20***	1.14**
	(0.03)	(0.05)	(0.07)
SIZE	0.97**	0.89***	0.94
	(0.01)	(0.02)	(0.04)
DIS	2.04***	1.75***	1.74**
	(0.15)	(0.24)	(0.39)
AMV	1.14***	1.32***	1.21**
	(0.03)	(0.06)	(0.11)
Constant	0.12***	0.16***	0.01***
	(0.04)	(0.09)	(0.01)

Note. This table provides the regression results for the aggregate market during the entire sample period (Model 1). It displays the relative risk ratios (RRR) and standard errors in parentheses of each variable in each *AVAR–GARCH* category. An RRR coefficient of less than 1 indicates that a firm was more likely to experience less-than-normal volatility, an RRR coefficient of 1 (or close to 1) shows that the independent variable had no effect on a firm's abnormal return volatility and an RRR coefficient greater than 1 denotes that a firm was more likely to experience abnormal return volatility. The abnormal return volatility (*AVAR–GARCH*) is classified into three categories: category 1 (low abnormal return volatility), 2 (moderate abnormal return volatility) and 3 (high abnormal return volatility). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

5.4.2 Economic Disruption Periods (Model 2)

Table 5.6 presents the results of Model 2, which shows the interaction between the economic disruption (*DIS*) variable with each independent variable. The interaction with each variable shows the additional impact of each independent variable on the likelihood of instigating abnormal return volatility specifically during economic disruptions. Overall, the results show that most variables did not elicit additional levels of abnormal return volatility during economic disruptions.

Specifically, only the SEO discount (*DISC*) and firm size (*SIZE*) instigated abnormal return volatility during economic disruptions. Although both were contributors to an increase in abnormal return volatility, *DISC* presented the highest statistically significant RRR in category 2, indicating that firms most likely experienced moderate levels of abnormal return volatility during economic disruptions. The fact that the SEO discount fell into category 2 for both Models 1 and 2 shows that the impact of the SEO discount remained the same during the entire sample period as well as during economic disruptions. This may not be ideal for firms that are trying to issue equity on multiple occasions. Thus, firms in this position should review the size of the discount continually to minimise its impact on shareholders. Sun et al. (2020) highlighted that large-capitalisation firms usually do not have a shortage of investors and therefore can still achieve a fully subscribed SEO with a smaller discount. This will have the benefit of minimising the degree of share ownership dilution and will therefore minimise the extent of abnormal return volatility.

Interestingly, the RRR for firm size (*SIZE*), which was less than 1 in Model 1 (0.90), turned to being greater than 1 (1.09) in Model 2 (category 1). This shows that during economic disruptions, larger firms were 1.09 times more likely to experience *low* albeit abnormal levels of return volatility, compared with less-than-normal volatility during the whole sample period.

These results are supported by Mikkelson and Partch's (2003) argument that shareholders react less favourably to larger firms issuing SEOs during economic disruptions. They further asserted that this negative reaction is because the assumption of large firms being 'safe and highly liquid' is being challenged. Hence, if firms begin issuing SEOs during economic disruptions, shareholders become increasingly concerned about the future viability of the firm.

In contrast, the market-to-book value (*MBV*) and abnormal trading volume (*AVOL*) presented RRR coefficients of less than 1, which indicates that they were associated with less-than-normal volatility during economic disruptions. This result is interesting because both variables had induced abnormal return volatility during the entire sample period (Model 1), but they reduced volatility in Model 2. This finding is consistent with Luo, Li and Liu's (2021) argument that the increased return volatility during higher market-to-book value periods reflects positive market sentiment, which results in greater participation during SEOs, translating into higher levels of volatility. Therefore, the opposite would be true during economic disruptions, which are characterised by low market-to-book value periods and a lower market sentiment. Thus, the participation rates also fall during SEOs, resulting in lower levels of volatility and therefore less trading volume.

Last, *AMV* produced the largest RRR coefficients in category 2, indicating that firms were most likely to experience moderate levels of abnormal return volatility. However, during economic disruptions (Model 2), this variable did not produce any statistically significant coefficients, indicating that *AMV* did not play a role in SEO-induced abnormal return volatility. Moreover, *ILLIQ* continued to produce a coefficient very close to 1, indicating that it had no effect on abnormal return volatility during economic disruptions.

Table 5.6: Model 2: Regression Results for Aggregate Market (Economic Disruptions)

	AVAR–GARCH Category		
	1	**2**	**3**
Variable	RRR	RRR	RRR
AVOL*DIS	**0.87****	**0.88**	**0.90**
	(0.06)	(0.08)	(0.09)
DISC*DIS	**0.96**	**1.18*****	**1.11**
	(0.07)	(0.07)	(0.16)
ILLIQ*DIS	**1.01****	**1.01****	**1.00**
	(0.00)	(0.00)	(0.00)
BAS*DIS	**1.02**	**0.93**	**0.95**
	(0.05)	(0.09)	(0.11)
MSA*DIS	**1.02**	**1.00**	**0.99**
	(0.02)	(0.03)	(0.03)
CIT*DIS	**1.11**	**0.79**	**0.96**
	(0.39)	(0.44)	(0.97)
COE*DIS	**1.01**	**1.01**	**0.98**
	(0.01)	(0.01)	(0.03)
MBV*DIS	**0.96**	**0.68****	**0.88**
	(0.10)	(0.11)	(0.20)
SIZE*DIS	**1.09***	**1.04**	**1.01**
	(0.06)	(0.09)	(0.09)
AMV*DIS	**0.96**	**0.91**	**0.85**
	(0.06)	(0.08)	(0.18)

Note. This table presents the regression results for economic disruptions (Model 2), which shows the interactions (in bold) of economic disruptions (*DIS*) with each independent variable as a separate regression, holding all other independent variables constant (a total of 10 independent regressions). The models were executed in this way to prevent the potential for multicollinearity of the *DIS* variable with other instances of *DIS* within the same regression. The results have been consolidated into one single table (above) with the standard errors in parentheses. It should be noted that the full factorial model was estimated, which includes each independent variable along with the interaction. For the purposes of brevity, only the interaction variables have been included to avoid extensively long results tables. The full results can be provided upon request. A relative risk ratio (RRR) less than 1 indicates that a firm was more likely to experience less-than-normal volatility, an RRR coefficient of 1 (or close to 1) indicates that the independent variable had no effect on a firm's abnormal return volatility and an RRR coefficient greater than 1 denotes that a firm was more likely to experience abnormal return volatility. Abnormal return volatility (*AVAR–GARCH*) is further classified into three categories: category 1 (low abnormal return volatility), category 2 (moderate abnormal return volatility) and category 3 (high abnormal return volatility). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

5.4.3 Robustness Test Results

To ensure the robustness of the findings, multiple specifications and proxies were applied to Models 1 and 2 across the aggregate market. First, both models were re-estimated under an alternate specification ‘vce(cluster)’, which allows for intragroup correlation by relaxing the requirement for each observation to be independent (Cameron & Miller 2015). For this research, this involved allowing clustering in the standard errors for each of the 31-day event windows. This specification was also used because it corrects for any potential correlation of observations within the 31-day event window. Table 5.7 presents the results of Models 1 and 2 under this specification, and it is confirmed that the coefficients and statistical significance of each coefficient is unchanged. The unchanged statistical significance confirms that the results of Models 1 and 2 are robust under the ‘vce(cluster)’ specification. The second robustness test applied was the replacement of the dependant variable, *AVAR–GARCH*, in Model 1 and 2 with an alternate measure, and it is confirmed that the independent variables remained statistically significant. The *AVAR–GJR–GARCH* proxy, which captures the leverage effect within the abnormal return volatility measure, confirms that the results remain robust even when using the *AVAR–GJR–GARCH*. Table 5.7 shows that the statistical significance of each independent variable remains unchanged. The third, and final, robustness test employed was the substitution of abnormal trading volume (*AVOL*) with abnormal turnover ratio (*ATR*), and of Amihud’s (2002) illiquidity ratio with Goyenko, Holden & Trzcinka’s (2009) Amivest liquidity ratio (*LIQ*). The results reported in Table 5.7 confirm that the statistical significance of each variable remains largely unchanged, and thus, the original results are robust. Notably, the RRR coefficients for *LIQ* were less than 1 but the RRR coefficients for *ILLIQ* were greater than 1. This is because the *ILLIQ* variable measures the degree of stock illiquidity, whereas *LIQ* measures the degree of stock liquidity, and therefore, an increase in *ILLIQ* (thus an increasing RRR greater than 1) is equivalent to a decrease in the RRR for *LIQ* (a decreasing

RRR less than 1). The statistical significance for *LIQ* remains consistent with *ILLIQ*, which confirms the robustness of the variable.

Table 5.7: Regression Results of Robustness Test (Entire Sample Period)

	Robustness Test 1			Robustness Test 2		
Category	**1**	**2**	**3**	**1**	**2**	**3**
Variable	RRR	RRR	RRR	RRR	RRR	RRR
AVOL	**1.23*** **	**1.30*** **	**1.32*** **	**1.23*** **	**1.30*** **	**1.32*** **
	(0.03)	(0.05)	(0.05)	(0.03)	(0.05)	(0.05)
DISC	**1.07*** **	**1.09*** **	**1.06**	**1.07*** **	**1.09*** **	**1.06**
	(0.02)	(0.03)	(0.06)	(0.02)	(0.03)	(0.06)
ILLIQ	**1.01*** **	**1.01*** **	**1.02*** **	**1.01*** **	**1.01*** **	**1.02*** **
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
BAS	**0.95** **	**0.99**	**0.92**	**0.95** **	**0.99**	**0.92**
	(0.02)	(0.03)	(0.05)	(0.02)	(0.03)	(0.05)
MSA	**1.01*** **	**1.02*** **	**1.01**	**1.01*** **	**1.02*** **	**1.01**
	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
CIT	**1.49*** **	**1.51* **	**1.05**	**1.49*** **	**1.51* **	**1.05**
	(0.20)	(0.37)	(0.42)	(0.20)	(0.37)	(0.42)
COE	**0.99*** **	**0.98*** **	**1.00**	**0.99*** **	**0.98*** **	**1.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
MBV	**1.10*** **	**1.20*** **	**1.14** **	**1.10*** **	**1.20*** **	**1.14** **
	(0.03)	(0.05)	(0.07)	(0.03)	(0.05)	(0.07)
SIZE	**0.97** **	**0.89*** **	**0.94**	**0.97** **	**0.89*** **	**0.94**
	(0.01)	(0.02)	(0.04)	(0.01)	(0.02)	(0.04)
DIS	**2.04*** **	**1.75*** **	**1.74** **	**2.04*** **	**1.75*** **	**1.74** **
	(0.15)	(0.24)	(0.39)	(0.15)	(0.24)	(0.39)
AMV	**1.14*** **	**1.32*** **	**1.21** **	**1.14*** **	**1.32*** **	**1.21** **
	(0.03)	(0.06)	(0.11)	(0.03)	(0.06)	(0.11)
Constant	**0.12*** **	**0.16*** **	**0.01*** **	**0.12*** **	**0.16*** **	**0.01*** **
	(0.04)	(0.09)	(0.01)	(0.04)	(0.09)	(0.01)

	Robustness Test 3		
Category	**1**	**2**	**3**
Variable	RRR	RRR	RRR
ATR	**1.16*** **	**1.23*** **	**1.27*** **
	(0.01)	(0.02)	(0.02)
DISC	**1.09*** **	**1.11*** **	**1.15*** **
	(0.02)	(0.03)	(0.05)
LIQ	**0.63*** **	**0.53*** **	**0.50*** **
	(0.01)	(0.02)	(0.02)
BAS	**1.00** **	**1.05**	**0.97**
	(0.02)	(0.03)	(0.05)
MSA	**1.01*** **	**1.02*** **	**1.01**
	(0.00)	(0.01)	(0.01)
CIT	**1.60*** **	**1.59* **	**0.85**
	(0.22)	(0.42)	(0.42)
COE	**0.99*** **	**0.98*** **	**0.99**
	(0.00)	(0.00)	(0.00)
MBV	**1.34*** **	**1.51*** **	**1.50*** **
	(0.04)	(0.07)	(0.10)
SIZE	**0.96** **	**0.90*** **	**0.93**
	(0.02)	(0.03)	(0.05)
DIS	**2.08*** **	**1.82*** **	**1.78** **
	(0.16)	(0.26)	(0.42)
AMV	**1.05** **	**1.20*** **	**1.09** **
	(0.03)	(0.06)	(0.10)
Constant	**2.94*** **	**5.85*** **	**1.33**
	(0.65)	(2.09)	(0.75)

Note. This table provides the regression results of each robustness test for the aggregate market during the entire sample period (Model 1). It displays the relative risk ratios (RRR) and standard errors in parentheses of each variable in each *AVAR–GARCH* category. An RRR coefficient of less than 1 indicates that a firm was more likely to experience less-than-normal volatility, an RRR coefficient of 1 (or close to 1) shows that the independent variable had no effect on a firm's abnormal return volatility and an RRR coefficient greater than 1 denotes that a firm was more likely to experience abnormal return volatility. The abnormal return volatility (*AVAR–GARCH*) is classified into three categories: category 1 (low abnormal return volatility), category 2 (moderate abnormal return volatility) and category 3 (high abnormal return volatility). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 5.7 Robustness Regression Test Results (Economic Disruptions) (Continued)

	Robustness Test 1			Robustness Test 2		
Variable	RRR	RRR	RRR	RRR	RRR	RRR
AVOL*DIS	**0.94*** **	**0.94***	**0.95**	**0.87** **	**0.87***	**0.90**
	(0.02)	(0.03)	(0.04)	(0.05)	(0.07)	(0.08)
DISC*DIS	**0.99**	**1.24** **	**1.13**	**0.96**	**1.17***	**1.11**
	(0.08)	(0.11)	(0.17)	(0.07)	(0.11)	(0.16)
ILLIQ*DIS	**1.01**	**0.95**	**0.97**	**1.01** **	**1.01*** **	**1.00**
	(0.02)	(0.03)	(0.05)	(0.00)	(0.00)	(0.00)
BAS*DIS	**0.99**	**0.88**	**0.89**	**1.02**	**0.93**	**0.96**
	(0.04)	(0.07)	(0.09)	(0.04)	(0.07)	(0.10)
MSA*DIS	**1.00**	**0.99**	**0.97**	**1.02**	**1.00**	**0.99**
	(0.01)	(0.02)	(0.04)	(0.01)	(0.02)	(0.03)
CIT*DIS	**0.87**	**0.63**	**1.10**	**1.10**	**0.82**	**0.97**
	(0.29)	(0.39)	(1.26)	(0.36)	(0.50)	(1.06)
COE*DIS	**0.98*** **	**0.98** **	**0.95** **	**1.01**	**1.01**	**0.98**
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
MBV*DIS	**1.25*** **	**1.03**	**1.38***	**0.95**	**0.71*** **	**0.87**
	(0.10)	(0.15)	(0.25)	(0.07)	(0.09)	(0.15)
SIZE*DIS	**0.97** **	**0.89*** **	**0.94**	**0.97** **	**0.89*** **	**0.94**
	(0.01)	(0.02)	(0.04)	(0.01)	(0.02)	(0.04)
AMV*DIS	**0.89***	**0.85***	**0.79**	**0.95**	**0.92**	**0.84**
	(0.06)	(0.08)	(0.17)	(0.06)	(0.08)	(0.16)

	Robustness Test 3		
Variable	RRR	RRR	RRR
ATR*DIS	**0.94*** **	**0.94**	**0.95**
	(0.02)	(0.03)	(0.04)
DISC*DIS	**0.99**	**1.24** **	**1.13**
	(0.08)	(0.11)	(0.17)
LIQ*DIS	**1.01***	**0.95** **	**0.97**
	(0.02)	(0.03)	(0.05)
BAS*DIS	**0.99**	**0.88**	**0.89**
	(0.04)	(0.07)	(0.09)
MSA*DIS	**1.00**	**0.99**	**0.97**
	(0.01)	(0.02)	(0.04)
CIT*DIS	**0.87**	**0.63**	**1.10**
	(0.29)	(0.39)	(1.26)
COE*DIS	**0.98**	**0.98**	**0.95**
	(0.01)	(0.01)	(0.02)
MBV*DIS	**0.75**	**0.97** **	**0.62**
	(0.10)	(0.15)	(0.25)
SIZE*DIS	**1.43*** **	**1.55**	**1.67**
	(0.03)	(0.05)	(0.09)
AMV*DIS	**0.89**	**0.85**	**0.79**
	(0.06)	(0.08)	(0.17)

Note. This table provides the regression results of each robustness test for the aggregate market during economic disruptions (Model 2), which shows the interactions (in bold) of economic disruptions (*DIS*) with each independent variable as a separate regression, holding all other independent variables constant (a total of 10 independent regressions). The models were executed in this way to prevent the potential for multicollinearity of the *DIS* variable with other instances of *DIS* within the same regression. The results have been consolidated into one single table (above) with the standard errors in parentheses. The full factorial model has been estimated, which includes each independent variable separated being specified along with its interaction with *DIS*. For the purposes of brevity, only the RRR coefficients of interaction variables have been included to avoid extensively long results tables. The full results can be provided upon request. A relative risk ratio (RRR) less than 1 indicates that a firm was more likely to experience less-than-normal volatility, an RRR coefficient of 1 (or close to 1) indicates that the independent variable had no effect on a firm's abnormal return volatility and an RRR coefficient greater than 1 denotes that a firm was more likely to experience abnormal return volatility. Abnormal return volatility (*AVAR–GARCH*) is further classified into three categories, denoting its level: category 1 (low abnormal return volatility), category 2 (moderate abnormal return volatility) and category 3 (high abnormal return volatility). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

5.5 Serial Correlation Analysis

Table 5.8 presents the results for the Wooldridge (2002) serial correlation test. Since the *p*-value is greater than 0.05, it can be confirmed that the idiosyncratic error term does not suffer from serial correlation. This is positive for the MLR model because the presence of serial correlation in the idiosyncratic error term would suggest that the standard errors are bias, which would mean the results are less efficient (Drukker 2003). The results of these preliminary tests confirm that the results of the MLR model can be relied upon.

Table 5.8: Serial Correlation Test Results

***F*-Statistic**	***p*-value**
0.024	0.8769

5.6 Summary

This chapter presented the first set of results of this thesis, which examines the determinants of abnormal return volatility across the Australian aggregate market. The chapter first discussed the descriptive statistics as well as the preliminary test results. The correlation matrix confirmed that the variables of interest do not suffer from multicollinearity and the unit root tests confirmed that the variables are stationary at levels. The main analysis consisted of two parts. In the first part (Phase 1), the findings supported the predictions under Hypothesis 1, in that SEO announcements did indeed impact abnormal return volatility, with the volatility being exacerbated during economic disruptions. As part of this analysis, comparisons were also drawn between the traditional *AVAR* measure and the improved proxies (*AVAR–GARCH* and *AVAR–GJR–GARCH*). The results showed that in many circumstances the abnormal return volatility was overstated in some years and understated in others by the traditional *AVAR* measure. This issue was caused by the traditional *AVAR* measure's reliance on the standard measure of variance measurement rather than conditional variance, which was solved by using the *AVAR–GARCH* proxy. This proxy allowed volatility clustering, which means that if volatility in the previous period was high (low), the volatility in the current period would also be high (low).

In the second part of the main analysis (Phase 2), two models were estimated. The results of the first model (entire sample period) identified that *AVOL*, *DISC*, *CIT*, *MBV*, *DIS* and *AMV* all elicited abnormal return volatility. In contrast, an increase in *BAS* and *SIZE* reduced the risk of firms experiencing abnormal return volatility. The second model presented the effect of each independent variable on abnormal return volatility during economic disruptions. The results showed that *DISC* and *SIZE* continued to instigate abnormal return volatility, whereas increases in *AVOL* and *MBV* resulted in firms experiencing less-than-normal volatility. Moreover, *AMV* instigated moderate levels of abnormal return volatility across the whole period but did not produce any statistically significant coefficients during economic disruptions, indicating that *AMV* did not play a significant role in abnormal return volatility during economic disruptions. Last, *ILLIQ* produced RRR coefficients close to 1 for both the entire sample period and periods of economic disruptions, indicating that it had no effect on abnormal return volatility during SEOs. The findings of this chapter show that *DISC* and *SIZE* need to be closely monitored by firms during SEOs since they elicited abnormal return volatility during the whole period as well as during economic disruptions. This finding offers an important policy implication that regulators may need to restrict the size of the discount for larger firms to help minimise their impact on abnormal return volatility. This chapter confirmed that each of the determinants have varied effects on a firm's abnormal return volatility across the aggregate market. Therefore, in the next chapter, further analysis is undertaken to understand which of these determinants play the largest role in influencing abnormal return volatility within each SEO type. This analysis will shed light on the more ideal SEO types that firms can choose, which will help them minimise abnormal return volatility when issuing equity capital.

Chapter 6: Abnormal Return Volatility and Its Determinants across SEO Types

6.1 Introduction

This chapter provides a comprehensive discussion of the results obtained from the econometric models for each SEO type described in Sections 4.2.2.2 (equation 1) and 4.2.2.3 (equation 13) of Chapter 4. In this chapter, RQ2 and RQ3 of this thesis are addressed and specified as follows:

RQ2: Which SEO types exhibit higher and lower levels of abnormal return volatility during SEO announcements?

RQ3: What are the determinants of the abnormal return volatility observed for each SEO type?

Section 6.2 first reports the descriptive statistics for each SEO type and also examines the trends observed in SEO choices by firms over time. The second half of the chapter discusses the Phase 1 and Phase 2 results for each SEO type. Section 6.3 presents the Phase 1 results which reports the changes in abnormal return volatility based on the traditional *AVAR* proxy, for each SEO type over time, with particular attention given to the three economic disruption periods. It also provides a comparison and an analysis of the traditional *AVAR* proxy with the improved *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies for each SEO type. Section 6.4 presents the Phase 2 results, which discusses the changes in abnormal return volatility based on the improved *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies as the regression dependant variables. This was done to understand the determinants of abnormal return volatility for each SEO type in Model 1 (entire sample period) and Model 2 (economic disruptions). Section 6.5 presents the results of the robustness tests performed to ensure that the regression results are reliable. The chapter concludes with section 6.6 discussing the implications of the results on a firm's SEO choices.

6.2 Descriptive Statistics

6.2.1 Descriptive Statistics for the Dependant and Independent Variables

Table 6.1 presents the summary statistics for the dependant and independent variables of each SEO type. Specifically, Section 6.2.1.1 covers the descriptive statistics for the various proxies representing the dependant variable and Section 6.2.1.2 describes the descriptive statistics for each independent variable.

6.2.1.1 Dependent Variable Proxies (AVAR, AVAR–GARCH and AVAR–GJR–GARCH)

Figure 6.1 shows the average abnormal return volatility (*AVAR*) in each year, for each of the nine SEO types across the entire sample period. It should be noted that although the traditional abnormal return volatility proxy, *AVAR*, is not carried through as the dependant variable in Phase 2 (MLR modelling), it is still used as a comparison and a reference point in Phase 1. Therefore, the descriptive statistics for this variable are retained in this section. The largest spikes in *AVAR* occurred during the 2008 GFC, the COVID-19 pandemic and 2012. During the GFC, all SEO types, except for placement & renounceable rights issue and standalone renounceable rights issue, experienced abnormal return volatility. During the COVID-19 period, placement & SPP and placement & non-renounceable rights issue produced the largest *AVAR* of approximately 3 and 5, respectively. The figure also shows a significant spike in *AVAR* occurring from 2012, which is, in part, due to the ASX (2012) implementing measures to help strengthen the equity-raising process in Australia's capital markets during this particular year. The main improvements included increasing capital limits for small and mid-size firms to 25%, updating ASX listing admission requirements and improving the disclosure documentation to investors. These measures saw a significant increase in SEO activity in 2012 and has resulted in sustained levels of SEO activity since. This increase can be observed through the multiple spikes in *AVAR* in 2012, 2015, 2016 and 2018.

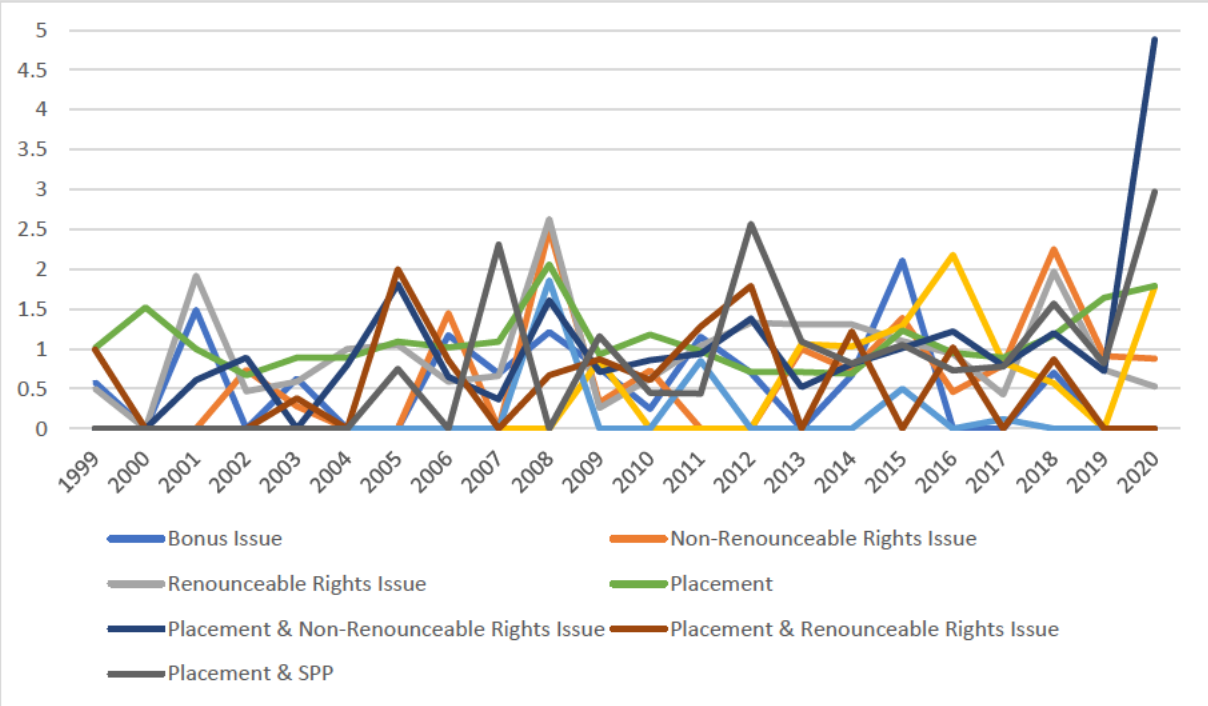


Figure 6.1: Abnormal Return Volatility (*AVAR*) by SEO Type

Note. This figure captures the average abnormal return volatility (*AVAR*) in each year, for each of the nine SEO types across the entire sample period. The classifications of the SEO types were sourced from Morningstar's classifications of equity issues.

As described in Table 6.1, the largest mean value for the traditional proxy of abnormal return volatility (*AVAR*) was observed for renounceable rights issue (1.48), whereas the lowest value was found for placement & non-renounceable rights issue (0.97), which incidentally was also the only SEO type to experience less-than-normal volatility (*AVAR* < 1). On comparing the mean values of the traditional abnormal return volatility proxy (*AVAR*) with those of the improved proxies (*AVAR–GARCH* and *AVAR–GJR–GARCH*), the values fell to below 1 across all SEO types, indicating that, on average, most SEO types instigate less-than-normal return volatility. However, the fact that the standard deviation for *AVAR–GARCH* and *AVAR–GJR–GARCH* across all SEO types, range between 1.16 and 2.50 indicates that some SEO types have the ability to experience abnormal levels of volatility, that is, up to 2.5 times higher than normal. The largest variability of 2.50 was identified in placement & non-renounceable rights issue, highlighting that firms that choose this SEO type are quite sensitive to SEO announcements. This SEO type also produced the largest mean value (0.86), indicating that it may not be an attractive option for firms. In addition to the high mean values of this SEO type, the non-renounceability associated with this SEO restricts retail shareholders from selling their ‘rights’ to a third party in the open market, making it less attractive to retail shareholders.

From the large kurtosis values for the abnormal return volatility proxies (*AVAR*, *AVAR–GARCH* and *AVAR–GJR–GARCH*) and *AVOL* across all sectors, it is evident that the data distribution is heavy tailed. Although heavy-tailed distributions can be deemed higher risk, they are also an inherent feature of financial asset data (Brennan & Subrahmanyam 1996). Alberg, Shialit and Yousef (2008) asserted that heavy tails are a sign of volatility clustering and leptokurtosis (observations that are clustered together, resulting in the peak/kurtosis to be substantially higher than a normal distribution) and are also commonly observed in financial asset data. All three abnormal return volatility proxies (*AVAR*, *AVAR–GARCH* and *AVAR–GJR–GARCH*) also exhibited a high positive skewness, which implies that in a distribution, the tail on the right-hand side is longer, and therefore, there are more observations aggregated on the left-hand side of the distribution. This high positive skewness observed is consistent with the fact that most of the abnormal return volatility values are closer to 0, with spikes in these values only occurring closer to the event day. Figure 6.2 shows the spikes in abnormal return volatility (*AVAR–GARCH*, presented as an example) typically occur during the [−3, +3] period of the entire 31-day SEO event window.

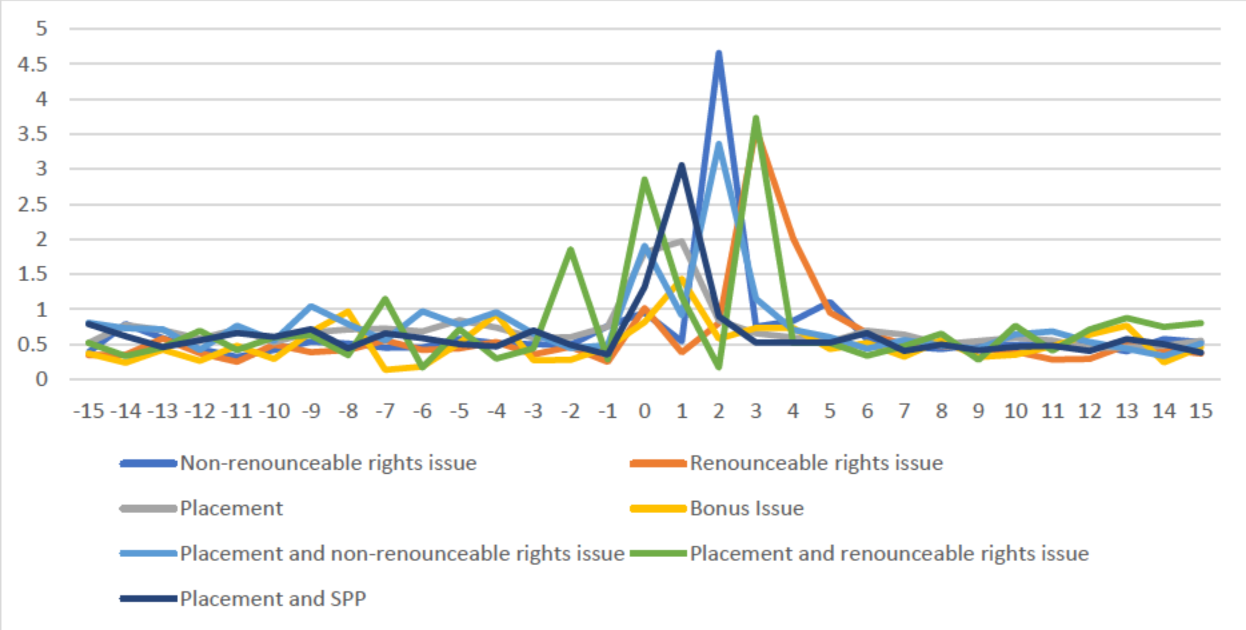


Figure 6.2 Average Daily *AVAR–GARCH* for Each SEO Type during the SEO Event Window

This figure captures the average abnormal return volatility for each day during the event window, for each SEO type across the entire sample period. The classifications of the SEO types have been sourced from Morningstar's classifications of equity issues.

6.2.1.2 Independent Variables

The highest mean values during periods in which placement & non-renounceable rights were issued were also recorded for many of the independent variables, including *AVOL*, *DISC*, *MSA*, *COE* and *AMV*. This is because the popularity of placement & non-renounceable rights issue increased sharply during 2009, which was characterised as a period of recovery following the GFC and therefore a period of low market volatility. Since this SEO type also experienced less-than-normal volatility across all three abnormal return volatility proxies, these variables do not appear to have posed an immediate risk to SEO-issuing firms, and therefore, should simply be monitored. Other notable outcomes include the highest mean being observed for (i) stock illiquidity when a placement & renounceable rights issue is issued; (ii) the bid–ask spread during a renounceable rights issue (iii) corporate insider trading and firm size for the period that a bonus issue is made and (iv) economic disruption value in placement & SPP.

As in the case of the *AVAR*, *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies, heavy-tailed distributions are also evident in *AVOL* and *ILLIQ*, presenting high kurtosis values across most sectors. The high kurtosis for *AVOL* is likely observed because of its causal relationship with *AVAR*, and it thus experiences a similar fat-tailed distribution (Shahzad et al. 2014). The large kurtosis for *ILLIQ* is likely due to the large spikes in stock illiquidity that occurred during economic disruptions, which result in a fatter tail distribution, relative to the low levels of stock illiquidity (*ILLIQ*) during normal economic periods (Fry 2018). Moreover, a high positive skewness is also observed in *AVOL* and *ILLIQ*, which implies that the right-hand tail in the distribution is longer and therefore more observations are observed on the left-hand side of the distribution. This again is also consistent with the fact that most of the *AVOL* and *ILLIQ* values are closer to 0, with spikes in these variables only occurring during the [−3, +3] period of the entire 31-day SEO event window.

Table 6.1: Descriptive Statistics for Each SEO Type

	Bonus Issue					Non-renounceable Rights Issue					Placement & Non-renounceable Rights Issue					Placement & Renounceable Rights Issue				
	Mean	**SD**	**Sk**	**K**	**Obs.**	**Mean**	**SD**	**Sk**	**K**	**Obs.**	**Mean**	**SD**	**Sk**	**K**	**Obs.**	**Mean**	**SD**	**Sk**	**K**	**Obs.**
AVAR	1.32	4.11	11.53	176.61	496	1.04	2.86	8.21	95.70	1,519	0.97	2.74	9.86	146.89	1,643	1.23	6.57	19.77	434.86	558
AVAR–GARCH	0.51	1.16	6.40	59.98	496	0.7	2.04	10.35	163.78	1,519	0.87	2.5	8.37	98.04	1,643	0.77	2.35	8.53	93.84	558
AVAR–GJR–GARCH	0.51	1.17	6.40	60.05	496	0.7	2.04	10.35	163.85	1,519	0.87	2.5	8.37	98.15	1,643	0.77	2.35	8.54	94.04	558
AVOL	1.13	1.13	5.79	53.20	496	1.51	1.99	7.34	98.84	1,519	1.81	2.08	4.50	35.19	1,643	1.71	3.53	11.57	188.40	558
DISC	N/A	N/A	N/A	N/A	N/A	0.46	1.31	3.40	13.41	1,519	1.25	2.71	2.57	9.60	1,643	0.94	2.27	2.49	7.55	558
ILLIQ	0.01	0.01	5.60	56.22	496	0.12	0.54	6.67	57.83	1,519	0.09	0.52	9.21	106.48	1,643	0.21	0.64	4.23	22.11	558
BAS	−3.14	1.59	0.95	3.13	496	−3.55	1.58	0.11	3.56	1,519	−3.43	1.35	0.26	4.27	1,643	−3.19	1.19	0.92	4.01	558
MSA	10.31	8.94	1.32	3.60	496	10.65	7.73	1.37	4.10	1,519	11.51	6.51	1.40	4.92	1,643	10.22	7.7	2.49	9.61	558
CIT	0.05	0.21	4.31	19.61	496	0.03	0.16	5.76	34.20	1,519	0.04	0.18	5.04	26.36	1,643	0.01	0.11	8.76	77.73	558
COE	0.26	0.05	1.51	4.57	496	0.25	0.12	2.10	13.23	1,519	0.29	0.11	−0.28	2.91	1,643	0.29	0.09	−0.62	4.24	558
MBV	0.9	0.71	0.10	1.46	496	0.52	1.02	1.21	4.79	1,519	0.39	1.23	0.53	5.44	1,643	0.73	0.67	0.23	1.53	558
SIZE	21.74	1.28	0.96	4.00	496	20.52	1.7	-1.07	3.60	1,519	20.52	2.14	-1.51	5.25	1,643	20.4	1.93	-0.55	3.24	558
DIS	0.13	0.33	2.27	6.14	496	0.1	0.29	2.75	8.58	1,519	0.06	0.24	3.72	14.83	1,643	0.06	0.23	3.88	16.06	558
AMV	0.83	0.72	1.90	7.96	496	0.76	0.73	2.07	9.27	1,519	0.83	0.77	2.02	9.04	1,643	0.74	0.71	1.94	7.98	558

Note. SD is the standard deviation, Sk is Skewness and K is Kurtosis. *AVAR* is the traditional abnormal return volatility proxy and is calculated as the average of the squared abnormal returns for the event window divided by the variance of returns during the estimation window; *AVAR–GARCH* and *AVAR–GJR–GARCH* are the improved abnormal return volatility proxies, measured as the average of the squared abnormal returns for the event window divided by the conditional forecasted variance during the estimation window. The calculation of the conditional variance in the *AVAR–GJR–GARCH* proxy also accounts for the leverage effect within the conditional variance component; *AVOL* is the abnormal trading volume, calculated as the daily trading volume during the SEO event window divided by the average trading volume during the estimation window; *DISC* refers to the SEO discount which is calculated as the difference between the SEO offer price and the closing share price, divided by the closing share price; *ILLIQ* is the stock illiquidity, which is the natural logarithm of 1 plus the absolute value returns divided by trading volume (in dollars); *BAS* is the bid–ask spread, which is calculated as the natural log of the difference between the ask price and the bid price; *MSA* refers to the number of market-sensitive announcements disclosed; *CIT* refers to corporate insider trading, which is a dummy variable that takes the value of 1 if corporate insiders engage in trading behaviour during the event window, and 0 otherwise; *COE* is the cost of equity capital, which is calculated as the square root of 1 divided by the PE growth ratio; *MBV* indicates the market-to-book value and is measured as the natural logarithm of the firm's market capitalisation divided by the book value; *SIZE* refers to the firm size, which is calculated as the natural logarithm of the share price multiplied by the number of shares outstanding; *DIS* is a dummy variable, which takes the value of 1 if there is an economic disruption period, and 0 otherwise; and *AMV* refers to the aggregate market volatility, which is calculated as the daily conditional variance (using GARCH (1,1) estimations) of the ASX 200 Index.

Table 6.1: Descriptive Statistics for Each SEO Type (Continued)

	Placement & SPP					Private Placement					Renounceable Rights Issue				
	Mean	**SD**	**Sk**	**K**	**Obs.**	**Mean**	**SD**	**Sk**	**K**	**Obs.**	**Mean**	**SD**	**Sk**	**K**	**Obs.**
AVAR	1.24	3.56	12.43	255.45	3,813	1.04	2.97	16.50	453.75	7,285	1.48	5.89	11.47	167.83	2,201
AVAR–GARCH	0.65	1.60	8.60	138.50	3,813	0.71	1.75	9.12	153.59	7,285	0.62	2.40	11.88	179.46	2,201
AVAR–GJR–GARCH	0.65	1.61	8.56	136.78	3,813	0.71	1.75	9.11	153.33	7,285	0.62	2.40	11.84	178.57	2,201
AVOL	1.52	1.62	5.90	64.69	3,813	1.49	3.20	16.51	379.74	7,285	1.30	1.75	11.65	235.96	2,201
DISC	0.16	0.85	8.20	73.60	3,813	0.19	0.99	8.76	101.96	7,285	0.43	1.52	5.75	35.27	2,201
ILLIQ	0.03	0.21	12.34	207.81	3,813	0.10	0.39	8.58	116.34	7,283	0.03	0.25	18.61	412.06	2,201
BAS	−2.96	1.61	0.10	2.64	3,813	−3.49	1.30	0.46	4.19	7,285	−2.69	1.47	0.83	4.15	2,201
MSA	8.54	5.91	1.80	7.58	3,813	10.77	7.55	1.44	5.79	7,285	9.39	8.10	2.24	8.99	2,201
CIT	0.03	0.17	5.49	31.19	3,813	0.02	0.13	7.44	56.30	7,285	0.03	0.17	5.61	32.42	2,201
COE	0.23	0.08	−0.15	5.39	3,813	0.26	0.17	7.54	95.12	7,285	0.25	0.08	−0.23	4.90	2,201
MBV	0.91	0.97	0.92	3.72	3,813	0.98	0.99	0.64	3.88	7,285	0.78	0.84	−0.57	5.36	2,201
SIZE	21.36	1.56	−0.28	3.51	3,813	20.49	1.93	−0.24	2.65	7,285	21.72	1.64	−0.23	3.43	2,201
DIS	0.19	0.39	1.61	3.61	3,813	0.10	0.30	2.64	7.97	7,285	0.07	0.26	3.30	11.92	2,201
AMV	0.77	0.90	3.79	26.59	3,813	0.76	0.75	2.83	18.48	7,285	0.71	0.65	2.30	14.79	2,201

Note. SD is the standard deviation; Sk is Skewness and K is Kurtosis. *AVAR* is the traditional abnormal return volatility proxy and is calculated as the average of the squared abnormal returns for the event window divided by the variance of returns during the estimation window; *AVAR–GARCH* and *AVAR–GJR–GARCH* are the improved abnormal return volatility proxies, measured as the average of the squared abnormal returns for the event window divided by the conditional forecasted variance during the estimation window. The calculation of the conditional variance in the *AVAR–GJR–GARCH* proxy also accounts for the leverage effect within the conditional variance component; *AVOL* is the abnormal trading volume, calculated as the daily trading volume during the SEO event window divided by the average trading volume during the estimation window; *DISC* refers to the SEO discount, which is calculated as the difference between the SEO offer price and the closing share price, divided by the closing share price; *ILLIQ* is the stock illiquidity, which is the natural logarithm of 1 plus the absolute value returns divided by trading volume (in dollars); *BAS* is the bid–ask spread, which is calculated as the natural log of the difference between the ask price and the bid price; *MSA* refers to the number of market-sensitive announcements disclosed; *CIT* refers to corporate insider trading, which is a dummy variable that takes the value of 1 if corporate insiders engage in trading behaviour during the event window, and 0 otherwise; *COE* is the cost of equity capital, which is calculated as the square root of 1 divided by the PE growth ratio; *MBV* indicates the market-to-book value and is measured as the natural logarithm of the firm's market capitalisation divided by the book value; *SIZE* refers to the firm size, which is calculated as the natural logarithm of the share price multiplied by the number of shares outstanding; *DIS* is a dummy variable, which takes the value of 1 if there is an economic disruption period, and 0 otherwise; and *AMV* refers to the aggregate market volatility, which is calculated as the daily conditional variance (using GARCH (1,1) estimations) of the ASX 200 Index.

Table 6.1: Descriptive Statistics for Each SEO Type (Continued)

	Renounceable & Non-renounceable Rights Issue					SPP				
	Mean	**SD**	**Sk**	**K**	**Obs.**	**Mean**	**SD**	**Sk**	**K**	**Obs.**
AVAR	2.37	4.76	2.82	10.33	62	0.80	1.25	3.25	17.71	217
AVAR–GARCH	1.01	2.16	3.12	12.70	62	0.41	0.75	3.67	20.63	217
AVAR–GJR–GARCH	1.01	2.16	3.12	12.69	62	0.41	0.75	3.66	20.59	217
AVOL	1.98	2.00	2.36	9.34	62	0.94	1.03	6.20	49.52	217
DISC	0.31	0.19	0.49	1.82	62	0.11	0.19	2.07	6.33	217
ILLIQ	0.04	0.08	2.32	8.49	62	0.13	0.92	12.92	180.74	217
BAS	−2.45	1.33	0.29	2.50	62	−3.36	1.58	0.43	2.12	217
MSA	12.50	7.56	0.00	1.00	62	9.86	4.20	0.19	2.38	217
CIT	0.22	4.21	18.72	0.25	62	0.02	0.13	7.16	52.27	217
COE	0.04	0.78	2.09	0.51	62	0.23	0.09	−0.89	2.06	217
MBV	1.02	−0.01	1.01	22.30	62	0.56	0.89	1.48	3.69	217
SIZE	0.47	0.02	1.48	0.00	62	20.83	1.62	−0.69	2.65	217
DIS	N/A	N/A	N/A	N/A	N/A	0.14	0.35	2.10	5.39	217
AMV	1.02	0.90	1.44	5.18	62	0.59	0.53	1.76	7.36	217

Note. SD is the standard deviation; Sk is Skewness and K is Kurtosis. *AVAR* is the traditional abnormal return volatility proxy and is calculated as the average of the squared abnormal returns for the event window divided by the variance of returns during the estimation window; *AVAR–GARCH* and *AVAR–GJR–GARCH* are the improved abnormal return volatility proxies, measured as the average of the squared abnormal returns for the event window divided by the conditional forecasted variance during the estimation window. The calculation of the conditional variance in the *AVAR–GJR–GARCH* proxy also accounts for the leverage effect within the conditional variance component; *AVOL* is the abnormal trading volume, calculated as the daily trading volume during the SEO event window divided by the average trading volume during the estimation window; *DISC* refers to the SEO discount, which is calculated as the difference between the SEO offer price and the closing share price, divided by the closing share price; *ILLIQ* is the stock illiquidity, which is the natural logarithm of 1 plus the absolute value returns divided by trading volume (in dollars); *BAS* is the bid–ask spread, which is calculated as the natural log of the difference between the ask price and the bid price; *MSA* refers to the number of market-sensitive announcements disclosed; *CIT* refers to corporate insider trading, which is a dummy variable that takes the value of 1 if corporate insiders engage in trading behaviour during the event window, and 0 otherwise; *COE* is the cost of equity capital, which is calculated as the square root of 1 divided by the PE growth ratio; *MBV* indicates the market-to-book value and is measured as the natural logarithm of the firm's market capitalisation divided by the book value; *SIZE* refers to the firm size, which is calculated as the natural logarithm of the share price multiplied by the number of shares outstanding; *DIS* is a dummy variable, which takes the value of 1 if there is an economic disruption period, and 0 otherwise; and *AMV* refers to the aggregate market volatility, which is calculated as the daily conditional variance (using GARCH (1,1) estimations) of the ASX 200 Index.

6.2.2 SEO Types Issued by Firms over Time

Table 6.2 provides a summary of the SEOs chosen by ASX 200 listed firms in 1999–2020, categorised by SEO type. The purpose of this table is to ascertain the most and least popular SEOs as well as uncover whether there are any noticeable trends in the types of SEOs that firms have used over time. Understanding any changes in the choice of SEO type is important in ascertaining whether firms favoured institutional investors (i.e. restricted SEOs) or included both institutional and retail shareholders (i.e. combined or standalone SEOs) during the equity-raising process.

Overall, this table shows that restricted SEOs were by far the most popular SEO choice, and private placements comprised approximately 41% of all SEOs in the study period. The second most popular SEO type was placement & SPP (categorised as a combined SEO), comprising approximately 21% of all SEO issuances. Despite these two SEOs accounting for approximately 62% of all SEOs, their popularity varied over time. For example, private placements dominated the SEO market from 1999–2012, suggesting that firms were focused solely on raising equity capital as quickly as possible, without considering the effect of this decision on retail shareholders. However, from 2013 onwards, the popularity shifted towards placement & SPP (a combined SEO), and it emerged as the preferred type. This shift was likely due to the ASX's (2020) commitment to promoting equality between institutional and retail shareholders in the equity-raising process. The least popular SEO types were renounceable & non-renounceable rights issue and standalone SPP. These SEO types did not become popular likely because firms preferred to maintain a dedicated institutional shareholder component in the SEO to expedite and streamline the equity-raising process, which these SEO types do not provide (Armitage & Snell 2001). Examples of SEO types that do provide a dedicated institutional shareholder component, and thus are more favoured by firms, include placement & non-renounceable rights issue, placement & renounceable rights issue and placement & SPP, which have become increasingly popular. Interestingly, standalone renounceable rights issues were more commonly and consistently used over the entire sample period than were the combined SEO, namely, placement & renounceable rights issue. This is likely because shareholders receive the offer of ‘renounceability’ on a rights issue very favourably, resulting in high SEO participation rates. Therefore, offering a dedicated institutional component (i.e. a combined SEO) is likely to be redundant. This is also beneficial to the firm raising capital because it can save the cost associated with offering the institutional component.

Table 6.2: Trends in SEOs for ASX 200 Firms

	Standalone SEOs					Restricted SEOs	Combined SEOs			
Year	Bonus Issue	Non-renounceable Rights Issue	Renounceable Rights Issue	SPP	Renounceable & Non-renounceable Rights Issue	Placement	Placement & Non-renounceable Rights Issue	Placement & Renounceable Rights Issue	Placement & SPP	Yearly Total
1999	1	1	3	0	0	10	0	1	0	16
2000	0	1	0	0	0	6	1	0	0	8
2001	0	1	1	0	0	17	1	2	0	22
2002	0	0	2	0	0	10	2	0	0	14
2003	0	1	1	0	0	14	0	1	1	18
2004	0	0	0	0	0	12	0	0	0	12
2005	0	1	3	0	0	7	0	1	1	13
2006	3	2	2	0	0	14	3	1	0	25
2007	1	0	4	0	0	17	0	0	3	25
2008	2	2	3	0	0	17	3	1	1	29
2009	1	8	4	1	0	29	14	5	4	66
2010	1	2	5	0	0	9	6	1	1	25
2011	1	1	6	0	0	13	2	0	1	24
2012	2	3	4	1	0	13	2	1	6	32
2013	0	1	5	0	0	9	1	1	11	28
2014	1	1	7	1	0	8	4	0	10	32
2015	2	4	8	1	1	11	1	0	11	39
2016	0	2	4	1	0	3	3	2	11	26
2017	0	9	1	1	1	5	2	1	12	32
2018	1	6	4	0	0	7	2	0	7	27
2019	0	1	2	1	0	5	6	0	21	36
2020	0	2	2	0	0	0	0	0	22	26
Total	16	49	71	7	2	236	53	18	123	575
Average	1.45	2.58	3.55	1	1	11.24	3.31	1.5	7.69	26.14
Median	1	2	3.5	1	1	10	2	1	6.5	25.5
Std. Dev.	0.69	2.46	1.96	0	0	5.79	3.26	1.17	6.84	11.97

Note. This table shows the total number of seasoned equity offerings (SEOs) issued by ASX 200 listed firms, for each SEO type.

6.3 Phase 1 Results: Measurement and Comparison of Abnormal Return Volatility Proxies across SEO Types

This section addresses RQ2 by discussing the results for the measurements and comparative analysis of the three abnormal return volatility proxies (*AVAR*, *AVAR–GARCH* and *AVAR–GJR–GARCH*). The purpose of this section is to understand the impact that SEO announcements have on abnormal return volatility for each SEO type and ascertain the similarities and differences across SEO types.

6.3.1 Hypothesis 2(a): Comparing Abnormal Return Volatility (Traditional Proxy – *AVAR*) across Each SEO Type

In this subsection, Hypothesis 2(a) is tested, which compares the abnormal return volatility observed across restricted, standalone and combined SEO types. As mentioned in Chapter 3, Hypothesis 2(a) is specified as follows:

> *H_{2a}: Firms that issue standalone or restricted SEOs experience higher abnormal return volatility than firms that issue combined SEOs.*

Table 6.3 presents the results of the average abnormal return volatility (based on the traditional proxy – *AVAR*) for each SEO type in each year. Overall, each SEO type did experience abnormal levels of return volatility in response to SEO announcements in at least a year during the sample period, although none experienced it consistently throughout the study period. A key observation however is that higher levels of abnormal return volatility were concentrated around the three economic disruptions than around normal operating periods, and variations also occurred across each SEO category (restricted, standalone and combined). Overall, restricted and standalone SEOs elicited higher levels of abnormal return volatility during the dot-com bubble and the GFC, whereas combined SEOs experienced higher levels during the COVID-19 pandemic. Notably, during the year 2000, many firms did not use standalone or combined SEOs (represented by the letter N in Table 6.3), but instead relied solely on private placements. This is because regulators did not focus on retail shareholder participation in SEOs during this time. However, over time, regulators and market makers have come to realise the importance of including retail investors in the equity-raising process to promote fairness and equality, which has subsequently led to a greater push for retail shareholder participation.[25] This was evident during the GFC and the COVID-19 pandemic, during which firms increased their reliance on standalone and combined SEOs, both of which include retail shareholders.

A closer examination of the first economic disruption (dot-com bubble) reveals that the largest *AVAR* was observed in standalone and restricted SEOs, which includes bonus issues, renounceable rights issues and private placements, which lends support to Hypothesis 2(a). In contrast, firms that issued combined SEOs during the dot-com bubble (i.e. placement & non-renounceable rights issue) experienced less-than-normal volatility, lending further support to Hypothesis 2(a). These results are consistent with Chung and Hwang's (2010) finding that restricted SEOs are more likely to elicit higher levels of volatility owing to the high degree of information asymmetry. The heightened information asymmetry arises from retail shareholders only acquiring knowledge of the private placement after it has already been completed, causing a larger investor reaction that leads to abnormal levels of return volatility during the SEO announcement. Similarly, in standalone SEOs, although institutional and retail investors can both partake, institutional investors usually purchase larger parcels of shares, which causes retail investors to be squeezed out of the SEO (Owen & Suchard 2008). Au Yong et al. (2021) confirmed that this squeezing out occurs in the Australian market by highlighting the participation rates of two types of standalone SEOs (standalone renounceable rights issue and standalone non-renounceable rights issue). Across both SEO types, 94% of institutional

[25] https://www2.asx.com.au/blog/importance-of-retail-investors-in-equity-capital-raisings

shareholders participated in SEOs, whereas only 64% of retail shareholders had the opportunity to participate. This practice shows that when a firm chooses to use a restricted or standalone SEO, retail shareholders are given either low or no priority in the process. Therefore, the significant increase in *AVAR* during the dot-com bubble is expected because it captures the negative sentiment of retail shareholders. With respect to combined SEOs, the lower *AVAR* is expected because investors have separate share allocations, because there is no competition between the institutional and retail shareholders (Dennis & Strickland 2002; Gabaix et al. 2006; Sias 1996; Xu, Y & Malkiel 2003). Consequently, combined SEOs are more likely to dampen the size of the negative reaction since retail shareholders are not unfairly disadvantaged.

During the second economic disruption (the GFC), standalone and restricted SEOs (private placements, renounceable rights issues, non-renounceable rights issues and renounceable & non-renounceable rights issues) also experienced the highest levels of *AVAR*, providing further support to Hypothesis 2(a). As in the case of the dot-com bubble, during the GFC as well, shareholders appeared to be slightly less sensitive to combined SEOs, as evidenced by a lower AVAR of 1.61 for placement & non-renounceable rights issues. Again, in this case, most firms chose to use private placements, which may not have been the most appropriate choice for it instigated higher levels of *AVAR*. Since the placement & renounceable rights issue exhibited less-than-normal volatility, this SEO type may have been a more appropriate choice. Interestingly, the opposing relationship was found for the COVID-19 pandemic, in which the highest *AVAR* was observed in combined SEOs (i.e. placement & non-renounceable rights issue and placement & SPP) rather than standalone SEOs, which does not support Hypothesis 2(a). In fact, when firms issued standalone SEOs (except for standalone SPPs), there was a reduction in return volatility. As highlighted in Table 6.2, this was likely due to the increase in the popularity of combined SEOs during the COVID-19 pandemic after the ASX (2020) introduced temporary emergency capital-raising measures. These measures allowed firms to raise a higher percentage of equity (from 15% to 25% through the institutional component only) than was allowed normally for a combined SEO. Retail shareholders of course viewed these measures less favourably because it meant that they would face a larger dilutive effect from the additional capital allocated to institutional shareholders.

In summary, the results show that standalone and restricted SEOs induced higher levels of *AVAR* during the dot-com bubble and the GFC, than they did during the COVID-19 pandemic. In contrast, *AVAR* was smaller for combined SEOs during the dot-com bubble and the GFC, but larger during the pandemic. This finding suggests that a shareholder's sensitivity to the type of SEO is affected by the type of economic disruption. These results differ from those of Ho et al. (2005) and Bae and Jo (1999), who either aggregated all SEOs together assuming that their effect on volatility was uniform or considered only one SEO type. By disaggregating SEOs into nine SEO types, greater insights were obtained about the behaviour of the individual SEO types. These results also highlight differences between standalone, restricted and combined SEOs in terms of abnormal return volatility. Last, the results of this study reinforce the findings of J Liu et al. (2016) who argued that some SEO types exhibit higher levels of volatility than others.

Table 6.3: Abnormal Return Volatility (*AVAR*) by SEO Type

Economic Disruption Period	Year	Standalone SEOs					Restricted SEOs	Combined SEOs		
		Bonus Issue	Non-renounceable Rights Issue	Renounceable Rights Issue	Security Purchase Plan	Renounceable & Non-renounceable Rights Issue	Placement	Placement & Non-renounceable Rights Issue	Placement & Renounceable Rights Issue	Placement & SPP
		AVAR	*AVAR*	*AVAR*	*AVAR*	*AVAR*	*AVAR*	*AVAR*	*AVAR*	*AVAR*
	1999	0.58	N	0.50	N	N	1.01	N	0.99	N
Dot-com bubble	2000	N	N	N	N	N	**1.52**	N	N	N
	2001	**1.49**	N	**1.92**	N	N	1.00	0.61	N	N
Normal operating period	2002	N	0.74	0.47	N	N	0.67	0.89	N	N
	2003	0.63	0.28	0.59	N	N	0.89	N	0.38	N
	2004	N	N	1.00	N	N	0.89	0.80	N	N
	2005	N	N	1.05	N	N	1.09	1.81	2.00	0.75
	2006	1.17	1.45	0.59	N	N	1.02	0.65	0.86	N
	2007	0.69	N	0.66	N	N	1.09	0.37	N	2.31
GFC	2008	**1.21**	**2.50**	**2.63**	N	**1.86**	**2.06**	**1.61**	0.67	N
Normal operating period	2009	0.76	0.33	0.26	0.86	N	0.93	0.71	0.87	1.16
	2010	0.25	0.73	0.63	N	N	1.18	0.86	0.61	0.45
	2011	1.15	N	1.04	N	0.85	0.97	0.94	1.28	0.44
	2012	0.70	N	1.33	N	N	0.71	1.38	1.79	2.57
	2013	N	1.00	1.31	1.06	N	0.71	0.52	N	1.09
	2014	0.67	0.72	1.31	1.03	N	0.69	0.81	1.22	0.82
	2015	2.11	1.39	1.10	1.29	0.50	1.23	1.01	N	1.05
	2016	N	0.46	0.94	2.18	N	0.95	1.22	1.02	0.73
	2017	N	0.8	0.43	0.83	0.12	0.89	0.79	N	0.78
	2018	0.70	2.25	1.97	0.57	N	1.17	1.20	0.87	1.57
	2019	N	0.91	0.74	N	N	1.64	0.72	N	0.82
COVID-19 pandemic	2020	N	0.88	0.53	**1.78**	N	**1.79**	**4.88**	N	**2.97**

Note. This table presents the results of the average *AVAR* in each year categorised by SEO type. The nine SEO types have been categorised based on Morningstar's classifications of equity issues. The values are interpreted as follows: if the value is below 1, this indicates that firms who chose the given SEO type experienced less-than-normal volatility, a value of 1 indicates that the SEO had no effect on the firm's return volatility and a value above 1 indicates that the SEO instigated an abnormal impact on the firm's return volatility. N indicates that no SEO was issued for the respective SEO type in the given year. The years during which an economic disruption occurred are highlighted in grey, and the values in bold pertain to the SEO types which experienced abnormal return volatility.

6.3.2 Comparing the Traditional *AVAR* Proxy to the Improved *AVAR–GARCH* and *AVAR–GJR–GARCH* Proxies across Each SEO Type

This subsection compares the abnormal return volatility values produced by the traditional *AVAR* proxy to those produced by the improved *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies across the SEO types. The purpose of this comparison is to understand whether the improved proxies reduce or exacerbate the size of abnormal return volatility of each SEO type. In Table 6.4, the traditional *AVAR* proxy and the improved *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies are reported to highlight their differences. Since it was established in the previous section that abnormal return volatility was concentrated primarily across the three economic disruptions, the comparisons between the traditional *AVAR* proxy and the improved *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies are also undertaken for these three disruption periods.

As shown in Table 6.4, the improved *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies produced more conservative measures of abnormal return volatility for some SEO types but more intensified for others, compared with the traditional *AVAR* proxy. Tsay (1987) highlighted that the conditional variance component of the *AVAR–GARCH* proxy uses the previous period's variance to determine the current period's variance, that is, volatility clustering. This feature makes it more accurate than the standard variance measurement that is used in the traditional *AVAR* proxy, which assumes that each period's variance is independent (Tsay 1987). As a result, for the SEO types that exhibited volatility clustering, the improved proxies estimated the abnormal return volatility to be higher than the traditional *AVAR* proxy (Schmitt & Westerhoff 2017). Conversely, for the SEO types that experienced a lower degree of volatility clustering, the improved proxies produced lower values for abnormal return volatility than the traditional *AVAR* proxy. Moreover, a comparison of the *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies with each other shows no substantial difference between their values. This implies that the leverage effect does not have a notable impact on abnormal return volatility. It should however be acknowledged that the *AVAR–GJR–GARCH* proxy produced similar values, which confirms that the *AVAR–GARCH* proxy is robust.

The largest difference between the traditional and improved abnormal return volatility proxies were found for placement & non-renounceable rights issues, for which *AVAR* produced a value of 4.88 whereas *AVAR–GARCH* produced a value of 1.95. This implies that the size of the abnormal return volatility is not as intense as initially suggested, signalling that volatility clustering is not as prominent in this SEO type. This may be because placement & non-renounceable issues require the firm to distribute a prospectus document, which provides relevant information about the SEO including the cost per share and the participation rights for each shareholder. The fact that more information is being shared contributes to a decrease in information asymmetry (Bradley & Yuan 2013). This leads shareholders to treat placement & non-renounceable issues more favourably, which results in lower levels of return volatility. This is a positive implication for firms that would not have initially considered this SEO type because they can now reconsider it as part of their SEO choice. Interestingly, this SEO type experienced the highest levels of abnormal return volatility during the COVID-19 pandemic, whereas those for renounceable rights issues were the lowest. However, the opposite was true during the dot-com bubble and the GFC. This finding shows that investor sensitivity to a particular SEO type can change depending on the nature of the economic disruption and that firms should be aware of the type of disruption occurring and adjust the SEO type being issued accordingly to suit the economic period (Dissanaike, Faasse & Jayasekera 2014; Xiao & Xi 2021).

In contrast, when firms announced a bonus issue during the dot-com bubble and the GFC, the abnormal return volatility estimated by the *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies was higher than that estimated using the traditional *AVAR* proxy. A similar finding was observed for renounceable rights issues during the dot-com bubble. These findings imply that the size of the abnormal return volatility is more intense than initially indicated by the traditional *AVAR* proxy, signalling that volatility clustering was more prominent for bonus issues and standalone renounceable rights issues during the dot-com bubble. Another interesting finding is that some SEO types (bonus issue, private placement, and placement & renounceable rights issue) produced values of less than 1, indicating that they were associated with less-than-normal volatility as measured by the traditional *AVAR* proxy. However, when estimated under the *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies for these SEO types, values greater than 1 were produced, indicating that they instigated abnormal levels of return volatility. This finding provides further validation that volatility clustering is prominent for these SEO types and that firms that are initially attracted to these SEOs because of their low (or less-than-normal) volatility may need to reconsider their SEO decisions.

In summary, it is evident that the improved proxies increased the accuracy of the measurement of abnormal return volatility. As highlighted by Tsay (1987), the improved proxies produced more accurate measurements of abnormal return volatility than did the traditional *AVAR* proxy because they use conditional variance to measure abnormal return volatility, rather than the standard variance measurement. Therefore, the improved proxies produced higher abnormal return volatility values for the SEO types with a higher degree of volatility clustering and a lower abnormal return volatility for SEO types with a lower degree of volatility clustering. The improved proxies, *AVAR–GARCH* and *AVAR–GJR–GARCH*, are therefore used as the dependant variable in the MLR model, which is covered in the discussion on Phase 1 presented in the following section. Specifically, *AVAR–GARCH* is used as the dependant variable in the base models and *AVAR–GJR–GARCH* is used as the dependant variable in the robustness tests.

Table 6.4: Comparison of *AVAR*, *AVAR–GARCH* and *AVAR–GJR–GARCH* during Economic Disruptions (by SEO Type)

Economic Period	Year	SEO Type	*AVAR*	*AVAR–GARCH*	*AVAR–GJR–GARCH*
Dot-com bubble	2000	Placement	1.52	0.91	0.91
	2001	Bonus Issue	1.49	3.21	3.18
		Placement	1.00	0.65	0.65
		Placement & Non-renounceable Rights Issue	0.61	0.57	0.57
		Renounceable Rights Issue	1.92	4.70	4.69
Global Financial Crisis	2008	Bonus Issue	1.21	1.73	1.73
		Non-renounceable Rights Issue	2.50	1.98	1.97
		Placement	2.06	1.60	1.59
		Placement & Non-renounceable Rights Issue	1.61	1.12	1.13
		Placement & Renounceable Rights Issue	0.67	0.46	0.46
		Renounceable & Non-renounceable Rights Issue	1.86	0.54	0.54
		Renounceable Rights Issue	2.63	2.50	2.49
COVID-19 pandemic	2020	Non-Renounceable Rights Issue	0.88	0.49	0.49
		Placement	1.79	1.51	1.53
		Placement & Non-Renounceable Rights Issue	4.88	1.95	1.95
		Security Purchase Plan	1.78	0.78	0.78

Note. This table compares the traditional *AVAR* proxy with the improved *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies. Classified by SEO type, these results focus on three economic periods of disruption (i.e. the dot-com bubble, the GFC and the COVID-19 pandemic). The values are interpreted as follows: if the value is below 1, this indicates that firms who chose the given SEO type experienced less-than-normal volatility, a value of 1 indicates that the SEO had no effect on the firm's return volatility and a value above 1 indicates that the SEO instigated an abnormal impact on the firm's return volatility.

6.4 Phase 2 Results: Determinants of Abnormal Return Volatility across SEO Types

This section addresses RQ3 by discussing the regression results for Phase 2, which examines the determinants and the degree to which these determinants affect abnormal return volatility (using the *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies) for each SEO type.

6.4.1 Hypothesis 3(a): Abnormal Trading Volume (*AVOL*)

Hypothesis 3(a) posits that an increase in *AVOL* results in an increase in abnormal return volatility across all SEO types. This argument assumes that *AVOL* and abnormal return volatility have a causal relationship (Shahzad et al. 2014). Table 6.5 shows that across the entire sample period, *AVOL* did indeed induce abnormal return volatility across all SEO types. Almost all SEO types produced the highest RRR coefficients in category 3, indicating that regardless of the SEO type chosen by a firm, they were most likely to experience the highest level of abnormal return volatility for every unit increase in *AVOL*. The only exception to this was placement & renounceable rights issue, which produced the highest RRR coefficient in category 2, indicating that firms still experienced *moderate* levels of abnormal return volatility when using this SEO type. These results are consistent with Morgan (1976) and Shahzad et al. (2014) who suggested that a rise in stock trading volume will be accompanied by an increase in return volatility. Shahzad et al. (2014) not only confirmed this positive relationship for ASX 200 listed stocks, but also asserted that the number of trades is the key component behind the increase in trading volume, which ultimately translates into higher return volatility.

Table 6.6 presents the regression results for each SEO type during economic disruptions. With respect to *AVOL*, only placement & non-renounceable rights issue and placement & renounceable rights issue continued to experience abnormal return volatility during economic disruptions. Interestingly, in Model 1 (Table 6.5), firms that chose placement & renounceable rights issue experienced *moderate* levels of abnormal return volatility across the entire sample period. However, firms that continued to use this SEO type during economic disruptions (Model 2: Table 6.6) experienced *high* levels of abnormal return volatility for each unit increase in trading volume. Dissanaike, Faasse and Jayasekera (2014) argued that firms experience higher levels of volatility during economic disruptions because investors are less concerned about the firm-level information disclosures and more concerned about poor macroeconomic conditions and identifying ways to counteract them. Au Yong et al. (2021) showed that shareholders achieve this by increasing their participation in combined SEOs with a rights issue component to avoid ownership dilution, which increases the trading volume exponentially. In contrast, three SEO types, standalone renounceable rights issue, private placement and placement & SPP produced coefficients of less than 1, indicating that for each unit increase in *AVOL* during economic disruptions, firms experienced less-than-normal volatility. This is an interesting result because in Model 1 (entire sample period), these SEO types all experienced high levels of abnormal return volatility. This may be because they do not provide the same benefits (renounceability and equality in participation between institutional and retail shareholders) as do combined SEOs with a rights issue component, as outlined by Au Yong et al. (2021), and thus will have lower participation rates by shareholders and ultimately lower trading volume during economic disruptions.

In line with these results, Hypothesis 3(a) is accepted for Model 1 because *AVOL* did instigate abnormal return volatility during the entire sample period across all SEO types. With respect to economic disruptions, since only some SEO types experienced abnormal return volatility, Hypothesis 3(a) is rejected for Model 2.

6.4.2 Hypothesis 4(a): SEO Discount (*DISC*)

Hypothesis 4(a) predicts that an increase in the SEO discount has a larger effect on abnormal return volatility for combined SEOs than for standalone SEOs and private placements. This hypothesis stems from the argument that low-performing firms are more likely to choose SEO types that offer larger discounts (combined SEOs) to incentivise shareholders to participate in the SEO (Certo, Holmes & Holcomb 2003; Jain & Kini, 1999; Patel, Emery & Lee 1993). This incentive increases the trading activity, ultimately leading to higher levels of volatility. Table 6.5 shows that across the entire sample period, for every 1% increase in the *DISC*, firms that chose combined SEOs (placement & non-renounceable rights issue and placement & SPP) did indeed experience high levels of abnormal return volatility. These findings are in line with S Xu, How and Verhoeven's (2017) argument that combined SEOs have a greater level of trading activity (particularly in Australia), and thus experience higher levels of return volatility. This is because the ASX (2020) actively promotes the use of combined SEOs by firms (through increasing equity-raising limits) to include retail shareholders in the equity-raising process. In contrast, private placements (restricted SEOs) produced an RRR coefficient of less than 1, indicating that an increase in the *DISC* reduces abnormal return volatility. These results are consistent with those of Barnes and Walker (2006), who argued that private placements experience a smaller negative reaction than SEOs consisting of a rights issue component (i.e. combined SEOs) owing to the smaller discount offered to institutional investors. These results indicate that if firms provide smaller discounts when using combined SEOs, it may help to minimise the degree of abnormal return volatility.

During economic disruptions (Model 2: Table 6.6), placement & SPP continued to experience abnormal return volatility, but it reduced to moderate levels. The fact that this SEO type instigated moderate levels of abnormal return volatility in both Models 1 and 2 suggests that it may not be the most ideal SEO type to use if a firm plans to provide a deep SEO discount to entice shareholder participation. Moreover, private placements experienced low levels of abnormal return volatility, but only during economic disruptions. This may be because retail shareholders penalised firms for offering large discounts to institutional shareholders during a period of economic uncertainty without providing retail shareholders the opportunity to participate, which is not advised by Australian regulators (The Treasury 2014). Thus, Hypothesis 4(a) is accepted for Model 1, but it is rejected for Model 2 because during economic disruptions, in addition to combined SEOs, private placements experienced abnormal return volatility for each unit increase in the *DISC*.

6.4.3 Hypothesis 5(a): Stock Illiquidity (*ILLIQ*)

Hypothesis 5(a) predicts that an increase in *ILLIQ* results in an increase in abnormal return volatility across all SEO types (Asem, Chung & Tian 2016; Qian 2011). This hypothesis is based on the expectation that when *ILLIQ* rises, shareholders are less concerned about the SEO type a firm has chosen and instead, more concerned about the risk of not being able to sell their holdings when they would ideally prefer to (Amihud & Mendelson 1986, 2015; Kyle 1985). Interestingly, Table 6.5 shows that across the entire sample period, the RRR coefficients for all SEO types were very close to 1 meaning each unit increase in the *ILLIQ* had no effect on abnormal return volatility. Unexpectedly, these results are opposed to those of Asem, Chung and Tian (2016) and Qian (2011), who asserted that *ILLIQ* and volatility are positively related. Nonetheless, these findings highlight that shareholders are not particularly concerned about changes in *ILLIQ* during SEO announcements for ASX 200 firms. Bilinski, Liu and Strong (2012) suggested that shareholders of larger firms (i.e. ASX 200 firms) are usually not concerned about changes in *ILLIQ* because they have a lower liquidity risk. This means that the likelihood of a large firm experiencing changes in *ILLIQ* that are severe enough to concern their shareholders is low and any increase in *ILLIQ* will be short-lived. Eckbo, Masulis and Norli (2000) also asserted that the issuance of SEOs helps to further lower the liquidity risk of firms.

In contrast, during economic disruptions (Table 6.6), all combined SEO types instigated abnormal levels of volatility, which indicates that shareholders became concerned about *ILLIQ* during periods of market uncertainty. Although *ILLIQ* affected all combined SEOs, firms that chose to use placement & renounceable rights issue experienced the highest levels of abnormal return volatility (highest RRR coefficient in category 3) for each unit increase in *ILLIQ*. The remaining combined SEOs (placement & non-renounceable rights issue and placement & SPP) produced the highest RRR coefficients in category 2, indicating that an increase in *ILLIQ* resulted in moderate levels of abnormal return volatility. These results are in line with Kothare's (1997) and Barnes and Walker's (2006) finding that firms that choose SEOs consisting of a higher institutional ownership concentration (i.e. private placement component) tend to experience higher levels of *ILLIQ* and therefore higher levels of return volatility. Last, notably, standalone private placements did not produce any statistically significant RRR coefficients, indicating that changes in *ILLIQ* during economic disruptions did not instigate a significant enough reaction by shareholders. Cronqvist and Nilsson (2005) argued that only smaller firms experiencing financial distress are more likely to choose standalone private placements during an economic crisis because it has a lower issuance cost to the firm. Since ASX 200 firms consist of the largest 200 firms by market capitalisation, it is not unexpected that private placements did not produce any statistically significant RRR coefficients.

In line with these results, Hypothesis 5(a) is rejected across the entire sample period (Model 1) for *ILLIQ* did not instigate abnormal return volatility within any SEO type. Moreover, Hypothesis 5(a) is also rejected for economic disruption periods (Model 2) because only combined SEOs experienced abnormal return volatility, rather than all SEO types as initially hypothesised.

6.4.4 Hypothesis 6(a): Information Asymmetry

Hypothesis 6(a) posits that an increase in information asymmetry (proxied by the bid–ask spread) results in a higher level of abnormal return volatility for SEO types consisting of an institutional component, that is, restricted and combined SEOs, compared with that for SEO types without a dedicated institutional component (i.e. standalone SEOs). This argument stems from existing studies suggesting that institutional (informed) shareholders possess superior information about a firm compared with retail (uninformed) shareholders (Chemmanur, He & Hu 2009; Cronqvist & Nilsson 2005; Krishnamurthy et al. 2005; Wu 2004). Institutional shareholders use this private information to purchase large blocks of shares during the SEO announcement period, which increases information asymmetry and may instigate abnormal levels of return volatility (Dierkens 1991; Sony & Bhaduri 2021).

Contrary to expectations, Table 6.5 shows that an increase in information asymmetry did not affect abnormal return volatility across the entire sample period for any SEO type. In fact, firms that used renounceable rights issues experienced less-than-normal volatility (RRR coefficient below 1) for each unit increase in information asymmetry. In contrast to existing studies (Chemmanur, He & Hu 2009; Cronqvist & Nilsson 2005; Dierkens 1991; Krishnamurthy et al. 2005; Sony & Bhaduri 2021; Wu 2004), the findings suggest that during the entire sample period, shareholders did not react to an increase in information asymmetry. This may be beneficial for firms that intend to issue equity during periods of high information asymmetry (during low information disclosure periods). Table 6.6 shows that during economic disruptions, two SEO types, standalone non-renounceable rights issue, and placement & SPP, both instigated high levels of abnormal return volatility. These results are consistent with existing research that cites a positive relationship between information asymmetry and return volatility (Chemmanur, He & Hu 2009; Cronqvist & Nilsson 2005; Dierkens 1991; Krishnamurthy et al. 2005; Sony & Bhaduri 2021; Wu 2004).

Therefore, Hypothesis 6(a) is rejected for Model 1, and it can be concluded that information asymmetry does not have a larger effect on firms that choose restricted and combined SEOs, over standalone SEOs. Hypothesis 6(a) is also rejected for Model 2 as the abnormal return volatility during economic disruptions was also not larger for firms that used restricted and combined SEOs instead of standalone SEOs. Although, there was one combined SEO type (placement & SPP) that did experience high abnormal return volatility, this finding was not consistent across all SEOs consisting of an institutional component. Although these results are unexpected, they nonetheless provide a positive outcome for firms because they do not need to be concerned about issuing SEOs during periods of high information asymmetry.

6.4.5 Hypothesis 7(a): Market-sensitive Announcements (*MSA*)

Hypothesis 7(a) states that firms who use SEO types associated with a larger number of market-sensitive announcements in the 6 months leading up to the SEO announcement, will experience higher abnormal return volatility. This is because when firms release multiple market-sensitive announcements regarding changes in business operations or profitability, shareholders become increasingly sensitive to each subsequent ASX disclosure (Lang & Lundholm 2000; Lin, YM, You & Lin 2008). Sourced from Table 4.2 in Section 4.2.2.2.2.1 of Chapter 4, the table below provides the total number of market-sensitive announcements issued by firms in the 6 months prior to an SEO announcement, categorised by SEO type.

Number of Market-sensitive Announcements

SEO Type	Number of Announcements
Private placement	3,118
Placement & SPP	1,198
Placement & non-renounceable issue	840
Renounceable rights issue	753
Non-renounceable rights issue	634
Placement & renounceable rights issue	217

Note. The number of announcements for each SEO type has been sourced from the dataset used in this thesis, which is originally from the Morningstar DatAnalysis database. This table has been sourced from Chapter 4. Further, only the SEO types for which multinomial logistic regression modelling (in Phase 2) was undertaken are included in this table.

The findings in Table 6.5 show that across the entire sample period, firms that chose standalone private placements, and placement & SPP were most likely to experience high and moderate levels of abnormal return volatility, respectively, for each additional *MSA* released in the 6 months prior to the SEO announcement. Given that these results align with the SEO types that had the largest number of market-sensitive announcements, Hypothesis 7(a) is accepted for

Model 1. This finding lends support to that of Prasad, Bakry and Varua (2020), who highlighted that market-sensitive announcements are positively related to stock return volatility. In contrast, firms that used placement & non-renounceable rights issue experienced less-than-normal volatility (RRR coefficient of less than 1), indicating that firms that chose this SEO type were not negatively affected by market-sensitive announcements disclosures. This is an unexpected result because out of the SEO types shown in the above table, firms that used placement & non-renounceable rights issue had the third largest number of market-sensitive announcements, which is in stark contrast to the finding of existing studies (Lang & Lundholm 2000; Lin, YM, You & Lin 2008). This may be because placement & non-renounceable issues require the firm to distribute a prospectus document, which provides relevant information about the SEO including the cost per share and the participation rights for each shareholder. The fact that information is being shared with shareholders leads them to treat placement & non-renounceable issues more favourably, which results in lower levels of return volatility. In contrast, SEOs consisting of an SPP do not require a prospectus to be issued, resulting in shareholders having less information about the SEO, which they are is likely to view negatively (Brown, Ferguson & Stone 2008).

Interestingly, during economic disruptions (Table 6.6), firms that used private placements, and placement & SPP did not experience abnormal return volatility for each additional market-sensitive announcement, despite their prominence in Model 1. Instead, standalone non-renounceable rights issue, placement & non-renounceable rights issue and standalone renounceable rights issue delivered RRR coefficients greater than 1, resulting in high, moderate and low levels of abnormal return volatility, respectively. It is also interesting to note that firms were more affected by SEOs for which a lower number of market-sensitive announcements were issued during economic disruptions. Y Zhang, Zhang and Seiler (2015) highlighted that firms that reduce their information disclosures tend to experience higher volatility. Lang and

Maffett (2011) further showed that the strength of this relationship increases during periods of economic disruptions.

As shown in the table above, since private placements, and placement & SPP, which also have the highest number of market-sensitive announcements, experience the highest levels of abnormal return volatility, Hypothesis 7(a) is therefore accepted for Model 1. However, Hypothesis 7(a) is rejected for Model 2 because firms associated with a lower number of market-sensitive announcements during economic disruptions were more likely than firms associated with a higher number of such announcements to experience abnormal return volatility.

6.4.6 Hypothesis 8(a): Corporate Insider Trading Behaviour (*CIT*)

Hypothesis 8(a) posits that *CIT* has a larger effect on a firm's abnormal return volatility that uses restricted SEOs, compared with that of combined and standalone SEOs. The basis of this argument is that institutional shareholders leverage *CIT* during SEOs to inform their own SEO investing decisions (through block trading) during a private placement, resulting in an increase in abnormal return volatility (Chen, A, Li & Chen 2001; Ching, Firth & Rui 2006; Cziraki, Lyandres & Michaely 2019; Hauser, Kraizberg & Dahan 2003; Lang & Lundholm 2000; Wang, J 1994).

Table 6.5 confirms that during the entire sample period, *CIT* did impact abnormal return volatility only for firms that chose private placements. Since the largest RRR coefficient was observed in category 1, this indicates that firms using private placements experienced a lower level of abnormal return volatility during *CIT*. These findings reaffirm the idea that institutional investors use *CIT* as a signal to either buy or sell shares during the SEO announcement (Chen, A, Li & Chen 2001; Ching, Firth & Rui 2006; Cziraki, Lyandres & Michaely 2019; Hauser, Kraizberg & Dahan 2003; Lang & Lundholm 2000; Wang, J 1994). Thus, Hypothesis 8(a) is accepted for Model 1.

Interestingly, Table 6.6 (Model 2) shows that during economic disruptions, only firms that chose non-renounceable rights issues were affected by *CIT*, experiencing high levels of abnormal return volatility. Since non-renounceable rights issues include retail shareholders in the SEO (in addition to institutional shareholders), when firms announce the use of this SEO type while corporate insiders are concurrently trading, retail shareholders react negatively. Aussenegg, Jelic and Ranzi (2018) argued that this effect may be due to corporate insiders exhibiting contrarian behaviour during economic disruptions. This involves directors selling their shares during high market sentiment periods and buying shares during low sentiment periods, which can result in a confusion in market sentiment and an increase in volatility (Van Geyt, Van Cauwenberge & Bauwhede 2013).

Moreover, interestingly, all the remaining SEOs produced statistically significant RRR coefficients lower than 1, indicating that *CIT* during economic disruptions (Model 2) is more likely to induce less-than-normal return volatility. In particular, the result for private placements was unexpected because it was in direct opposition to the findings observed in Model 1. Nonetheless, it suggests that investors appear to be less concerned about insider trading during an economic crisis. Tamersoy et al. (2014) highlighted that the low volatility is because insiders' trading activity drops to low (almost zero) levels during economic disruptions. The authors asserted that it is because directors have already largely exited their position prior to the onset of the economic crisis and therefore do not engage in trading during an economic crisis. Therefore, Hypothesis 8(a) is rejected for Model 2.

6.4.7 Hypothesis 9(a): Cost of Equity Capital (*COE*)

The *COE* had a rather mixed effect across each SEO type during the entire sample period and economic disruption periods. Hypothesis 9(a) posits that an increase in the *COE* for issuing SEOs consisting of rights issues results in higher abnormal return volatility, compared with that of SEO types without a rights issue component. The premise of this hypothesis is that rights issues are associated with higher retail shareholder participation rates, resulting in firms incurring a higher *COE* (Au Yong et al. 2021). This is because retail shareholders purchase a smaller number of shares and have a lower risk tolerance, compared with institutional shareholders, and therefore, firms will incur a higher *COE* to compensate retail shareholders for the risk they take (Attig et al. 2013; Kannadhasan 2015). Thus, the increase in this *COE* will translate into higher levels of volatility.

Table 6.5 presents the impact of the *COE* on abnormal return volatility across the entire sample period. The results highlight that an increase in the *COE* instigated abnormal return volatility across all almost SEOs consisting of rights issues or a rights issue component. Of these SEO types, combined SEOs experienced the highest level of abnormal return volatility (highest RRR coefficients in category 3), whereas standalone renounceable rights issues fell into category 1, indicating low levels of abnormal return volatility. These results are consistent with W Zhang's (2014) suggestion that an increase in the *COE* will translate into higher levels of volatility. These findings also lend support to Au Yong et al. (2021), who argued that SEOs that include a rights issue component are most likely to experience the highest levels of volatility. The only exception was standalone non-renounceable rights issues, which produced an RRR coefficient close to 1, indicating that an increase in the *COE* had no effect on this SEO type. Moreover, as expected by Hypothesis 9(a), firms that chose SEOs without a rights issue component (i.e. placement & SPP, and private placements) experienced less-than-normal volatility for each unit increase in *COE*. These results highlight that when a firm's *COE* increases, SEOs that include a rights issue component (except for standalone non-renounceable rights issues) will experience abnormal levels of return volatility, whereas those without a rights issue component will not.

Table 6.6 shows that the results for Model 2 remain consistent, in that firms that chose SEOs consisting of a rights issue component continued to experience abnormal levels of volatility during economic disruptions (Model 2). In fact, renounceable rights issues produced the largest coefficient in category 3 (upgraded from category 1 in Model 1), indicating that the abnormal return volatility was exacerbated during economic disruptions for each unit increase in the *COE*. These findings are in line with that of Duffee (1995), who showed that the reaction to SEO announcements is amplified during economic crisis, resulting in greater levels of uncertainty and volatility. In line with these results, Hypothesis 9(a) is accepted for both Models 1 and 2.

6.4.8 Hypothesis 10(a): Market-to-Book Value (*MBV*)

Hypothesis 10(a) predicts that an increase in the *MBV* has a similar effect on the abnormal return volatility of all firms, irrespective of the SEO type chosen. Since *MBV* is a measure of whether a firm is overvalued or undervalued, if a firm undertakes an SEO during an overvalued period (high *MBV*), shareholders will flock to buy slightly discounted shares, resulting in an increase in volatility (Fama & French 1995). J Chen, Chollete and Ray (2010) argued that despite the shares being overvalued, the 'fear of missing out' leads shareholders to participate in the SEO, regardless of the SEO type chosen by the firm

Table 6.5 shows that during the entire sample period, this was true for all SEO types except placement & SPP. As regards the affected SEO types, renounceable rights issue, placement & non-renounceable rights issue, and placement & renounceable rights issue produced the highest RRR coefficients in category 3, indicating that firms that chose these SEO types were most likely to experience high levels of abnormal return volatility. Firms that chose private placements experienced moderate levels of abnormal return volatility. These results indicate that regardless of whether a firm chooses a restricted, standalone or combined SEO, all these SEO types are likely to instigate abnormal return volatility in the presence of an increasing *MBV*. These findings are consistent with that of Fama and French (1995), who suggested that high-*MBV* firms are more likely to experience higher volatility. The fact that abnormal return volatility was observed in almost all SEO types also lends support to J Chen, Chollete and Ray's study (2010), which highlighted that during overvalued periods, shareholder participation rates in SEOs increase, regardless of the SEO type chosen by the firm. The only exception noted was in placement & SPP, for which no statistically significant RRR coefficient was observed.

During economic disruptions (Table 6.6), renounceable rights issues and non-renounceable rights issues continued to experience abnormal return volatility. Although that of non-renounceable rights issues remained at high levels, the abnormal return volatility of renounceable rights issues fell from high (in Model 1) to low levels, indicating that shareholders view renounceable rights issues slightly more favourably during economic disruptions. These results are consistent with that of Balachandran et al. (2008), who argued that investors view renounceable rights issues more favourably than non-renounceable rights issues. Interestingly, placement & SPP experienced high levels of abnormal return volatility during economic disruptions, whereas in Model 1, this type did not produce any statistically significant RRR coefficients. This result may be attributable to the increased use of this SEO type because of ASX (2010, 2012, 2020) promoting it over standalone private placements during the GFC and the COVID-19 pandemic, to include retail shareholders in the equity-raising process. Moreover, firms that used placements, placement & non-renounceable rights issue, and placement & renounceable rights issue during economic disruptions all experienced less-than-normal volatility, whereas in Model 1, these types all instigated abnormal return volatility. This finding indicates that these SEO types may be better suited for use only during economic disruptions. In line with these findings, Hypothesis 10(a) is rejected for both Models 1 and 2, and it can be concluded that an increase in the *MBV* instigates various levels of abnormal return volatility in most SEO types, although there is no identifiable trend.

6.4.9 Hypothesis 11(a) and 11(b): Firm Size (*SIZE*)

Hypothesis 11(a) states that an increase in firm size induces less-than-normal volatility in all SEO types. The lower volatility stems from the belief that the future performance of larger firms has greater certainty and that they have a lower likelihood of experiencing financial distress; thus, they are considered lower risk (Chan, KC & Chen 1991; Chen, N & Zhang 1998; Fama & French 1992; Vassalou & Xing 2004). Table 6.5 confirms this expectation in that larger firms were more likely to experience less-than-normal volatility across all SEO types, evident through the RRR coefficients being lower than 1. These findings support the assertion of Banz (1981), Reinganum (1981) and Drew (2003) that there is a negative relationship between *SIZE* and volatility. Therefore, Hypothesis 11(a) is accepted for Model 1.

Hypothesis 11(b) predicts that larger firms that choose SEO types with greater shareholder restrictions (non-renounceability) and less fairness (standalone SEOs) during economic disruptions, experience higher abnormal return volatility than do larger firms that choose SEOs with greater shareholder flexibility (renounceability) and fairness (combined SEOs). The findings in Table 6.6 confirm that during economic disruptions, larger firms were more likely to experience abnormal return volatility if they chose an SEO type with restrictions imposed on it (i.e. non-renounceability in a rights issue) or an SEO type that requires retail shareholders to compete with institutional shareholders (i.e. standalone SEOs) and therefore is less fair to retail shareholders. More specifically, non-renounceable rights issues experienced high levels of abnormal return volatility (category 3), whereas renounceable rights issues experienced low levels of abnormal return volatility (category 1). These results are consistent with Balachandran et al.'s (2008) finding that investors view renounceable rights issues more favourably than they do non-renounceable rights issues. Interestingly, although firms that used private placements were expected to experience higher levels of abnormal return volatility, they also experienced low levels of abnormal return volatility (category 1).

Moreover, during economic disruptions, combined SEOs were expected to elicit the lowest levels of volatility, which was the case for placement & renounceable rights issue, which produced an RRR of less than 1. This is likely because combined SEOs provide a separate share allocation for institutional and retail investors, which promotes fairness in participation and therefore is viewed favourably by shareholders (Dennis & Strickland 2002; Gabaix et al. 2006; Sias 1996, Xu, Y & Malkiel 2003). Moreover, the fact that renounceability is offered is a positive signal to retail shareholders, for it allows them the opportunity to sell their rights (to minimise ownership dilution), if they do not wish to participate in the SEO, and therefore minimise the extent of dilution in their ownership percentage (Balachandran et al. 2008). Firms that chose placement & SPP did also experience abnormal return volatility, but at low levels. This may be because this SEO type has the benefit of a combined SEO whereby institutional and retail shareholders have separate share allocations, and therefore, retail shareholders do not need to compete with institutional shareholders. However, the downside to including an SPP component is that it allows existing shareholders to purchase up to AUD30,000 worth of shares per investor, which can cause a substantially larger degree of ownership dilution than a rights issue (which is offered on a pro-rata basis rather than a fixed dollar amount) (ASIC 2019). Therefore, since larger firms that chose SEO types with more restrictions and less fairness for retail shareholders experienced higher levels of abnormal return volatility during economic disruptions, Hypothesis 11(b) is accepted.

6.4.10 Hypothesis 12(a): Aggregate Market Volatility (*AMV*)

Hypothesis 12(a) posits that an increase in *AMV* will elicit a similar effect on abnormal return volatility across all firms irrespective of the SEO types chosen. This relationship is expected because there is a positive correlation between individual firm volatility and *AMV*, which does not vary according to the SEO type chosen by firms and also becomes stronger during economic disruptions (Campbell et al. 2001).

Table 6.5 shows that the effect of *AMV* on the abnormal return volatility for each SEO type was mixed. During the entire sample period, *AMV* instigated either low or moderate levels of abnormal return volatility across all SEO types except for placement & non-renounceable rights issue. Apart from the results for this SEO type, these results are consistent with that of Sharma, Narayan and Zheng (2014), who argued that *AMV* does instigate higher firm-level volatility.

As Table 6.6 shows, only two SEO types, non-renounceable rights issue and placement & SPP, continued to instigate abnormal return volatility during economic disruptions. Interestingly, all other SEO types that elicited abnormal return volatility across the entire sample period (Model 1), produced RRR coefficients of less than 1 during economic disruptions (Model 2). These SEO types included private placement, placement & non-renounceable rights issue, and placement & renounceable rights issue, highlighting that an increase in *AMV* reduced the relative risk of experiencing abnormal return volatility for firms that chose these SEO types. These results oppose the findings of Campbell et al. (2001), who suggested that the correlation between market movements and individual stock movements increase during economic disruptions. However, the fact that there were a smaller number of SEO types that were affected by an increase in *AMV* during economic disruptions lends support to Schill (2004), who suggested that investors are less likely to participate in SEOs during high volatility periods.

According to these results, Hypothesis 12(a) is rejected for both Models 1 and 2 because only some SEOs were affected by *AMV*.

Table 6.5: Model 1 – Summary of Regression Results for each SEO Type (Entire Sample Period)

	Standalone SEOs						Restricted SEOs			Combined SEOs								
	Renounceable Rights Issue			Non-renounceable Rights Issue			Placement			Placement & Non-renounceable Rights Issue			Placement & SPP			Placement & Renounceable Rights Issue		
Category	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Variable	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR
AVOL	1.24***	1.47***	1.61**	1.35***	1.42***	1.45***	1.15***	1.18***	1.20***	1.14***	1.30***	1.54***	1.48***	1.61***	1.76***	1.12*	1.26***	1.25***
DISC	1.11	0.96	0.83	1.00	1.10	0.96	1.04	1.05	0.75**	1.04	1.08*	1.25***	1.18***	1.23***	1.43***	0.86	0.06	0.08
ILLIQ	1.04***	1.04***	1.04**	1.02***	1.02***	1.02***	1.01***	1.01***	1.02***	1.01***	1.02***	1.02***	1.01***	1.01***	1.02***	1.01***	1.02***	1.01***
BAS	0.78***	0.81	1.04	0.95	1.06	0.84	1.05	1.07	1.05	0.92	1.01	0.89	1.03	1.06	0.93	0.83	0.75	0.96
MSA	0.99	1.00	0.99	1.00	0.99	0.98	1.01**	1.02**	1.04***	1.00	1.02	0.86***	1.03***	1.04***	1.03	1.01	1.12	0.91
CIT	1.00	1.14	0.75	1.00	0.78	0.00	2.99***	2.13*	1.28	1.08	1.00	0.51	0.85	1.76	0.64	0.00	3.16	0.00
COE	1.04**	1.01	1.02	0.97***	0.96***	0.98	0.99**	0.98***	1.01	1.02*	1.03**	1.10***	1.00	0.97*	0.97	1.04**	1.06**	1.09***
MBV	1.54***	1.66***	1.95**	1.13	1.27**	1.42*	1.10**	1.18**	1.21	0.87*	1.21	1.75**	1.03	1.02	0.86	2.02**	1.94	3.60*
SIZE	0.89*	0.80	0.75	1.00	0.99	1.07	0.96*	0.88***	0.90	1.27***	1.21**	1.31**	0.89***	0.78***	0.82	1.02	0.98	0.69
DIS	3.81***	0.89	1.35	3.84***	1.15	0.00	1.89***	1.86***	3.45***	1.66*	1.96	2.78	1.70***	1.59*	1.10	2.83*	2.65	10.76
AMV	1.05	1.58**	0.97	1.37**	1.08	0.41*	1.10*	1.42***	1.23	1.04	1.09	0.96	1.11*	1.16*	1.23	2.01***	1.41	1.37
Constant	0.10	0.24	1.04	0.07*	0.07	0.00*	0.26**	0.35	0.03**	0.00***	0.00***	0.00***	0.52	3.68	0.20	0.00**	0.00	0.48

Note. This table provides the regression results for each SEO type across the entire sample period (Model 1). It displays the relative risk ratios (RRR) of each variable for each *AVAR–GARCH* category. An RRR coefficient of less than 1 indicates that a firm was more likely to experience less-than-normal volatility, an RRR coefficient of 1 (or close to 1) shows that the independent variable had no effect on a firm's abnormal return volatility and an RRR coefficient greater than 1 denotes that a firm was more likely to experience abnormal return volatility. The abnormal return volatility (*AVAR–GARCH*) is classified into three categories: category 1 (low abnormal return volatility), 2 (moderate abnormal return volatility) and 3 (high abnormal return volatility). The standard errors have been included in the Appendices. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 6.6: Model 2 – Summary of Regression Results for each SEO Type (Economic Disruptions)

	Standalone SEOs						Restricted SEOs			Combined SEOs								
	Renounceable rights issue			Non-renounceable rights issue			Placement			Placement & non-renounceable rights issue			Placement & SPP			Placement & renounceable rights issue		
Category	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Variable	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR
AVOL	1.33***	1.50**	1.67**	1.36***	1.42***	1.46***	1.18***	1.21***	1.24***	1.13***	1.30***	1.52***	1.58***	1.75***	1.94***	1 10	1.25***	1.24***
DIS	7.43***	0.64	3.10	5.08***	0.86	0.00***	2.41***	2.48***	3.89***	0.88	1.29	0.51	2.60***	2.81***	2.74	0 15	0.21	0.35
AVOL*DIS	**0.64****	**0.95**	**0.73**	**0.82**	**1.13**	**0 89**	**0.86****	**0.85****	**0.90**	**1.52***	**1.34**	**2.09****	**0.79***	**0.76***	**0.72****	**17.89****	**13.37****	**20.28****
DISC	1.11*	0.96	0.84	1.00	1.10	0 97	1.03	1.04	0.76**	1.03	1.05	1.25***	1.18***	1.21***	1.43***	0.89	0.16	0.69
DIS	11.50***	6.50*	10.42*	6.63***	1.44	0.00***	1.55***	1.41	3.83***	1.21	0.76	2.98	1.44*	0.62	0.56	5 98	8.73***	2.12**
DISC*DIS	**0.00****	**0.00****	**0.00**	**0.00**	**0.15**	**18.44**	**3.90***	**5.81**	**0.51**	**1.14**	**1.35**	**0.99**	**5.91**	**3.59*****	**652.71**	**0.01**	**0.00*****	**0.00***
ILLIQ	1.04***	1.04***	1.03**	1.01***	1.02***	1.02***	1.01***	1.01***	1.02***	1.01***	1.02***	1.02***	1.01***	1.01***	1.02***	1.01***	1.02***	1.01***
DIS	3.72***	0.91	1.29	3.11***	0.44	0.00***	1.84***	1.75**	3.10***	1.12	0.62	2.93	1.29	0.93	0.77	2 22	0.70	1.63
ILLIQ*DIS	**1.02**	**0.98**	**1.04**	**1.01**	**1.02****	**0 98*****	**1.00**	**1.00**	**1.00**	**1.04*****	**1.07*****	**0.98**	**4.17*****	**9.16*****	**5.61*****	**11.44**	**11.74**	**19.72****
BAS	0.74***	0.81	1.08	0.96	1.08	0.84	1.05	1.06	1.08	0.91	1.04	0.90	1.01	1.07	0.80	0 90	0.92	0.98
DIS	6.32***	0.80	0.43	3.03*	0.39	0.00***	2.24***	2.11*	2.32	2.09	0.85	2.62	1.96***	1.51	4.17*	0.09	0.00***	9.59
BAS*DIS	**1.27**	**0.95**	**0.65**	**0.92**	**0.71**	**1 50***	**1.06**	**1.04**	**0.89**	**1.07**	**0.79**	**0.98**	**1.08**	**0.98**	**1.99****	**0 34**	**0.00*****	**0.96**
MSA	0.77***	0.81	1.04	1.00	0.99	0 98	1.01	1.02**	1.04***	1.00	1.01	0.89***	1.04***	1.04***	1.03	1.01	1.12	0.91
DIS	1.88	1.73	2.04	3.04*	11.89**	0.00***	1.56**	1.74*	3.41***	1.53	0.15	11.48	1.97***	2.02*	2.45	2.83*	2.65	10.76
MSA*DIS	**1.08****	**0.86**	**0.91**	**1.03**	**0.69****	**1 15***	**1.03**	**1.01**	**1.00**	**1.01**	**1.18****	**0.89**	**0.98**	**0.96**	**0.87**	**1.00**	**1.00**	**1.00**
CIT	1.14	1.20	0.80	1.29	0.91	0.00***	2.83***	2.75**	1.95	1.17	1.10	0.14	0.88	1.61	0.84	0.00***	4.65	0.00***
DIS	3.93***	0.91	1.38	4.04***	1.21	0.00***	1.86***	1.93***	3.60***	1.72*	2.08*	2.17	1.70***	1.56	1.15	2.87**	3.40	10.79
CIT*DIS	**0.00*****	**0.00*****	**0.00*****	**0.36**	**0.00*****	**2 18*****	**1.21**	**0.31**	**0.00*****	**0.54**	**0.00*****	**18 20**	**0.89**	**1.31**	**0.00*****	**0 92**	**0.00*****	**0.98**
COE	1.03**	1.01	1.02	0.97**	0.96**	0 98	0.99**	0.98***	1.02*	1.02*	1.03**	1.09***	0.99	0.97*	0.98	1.04**	1.06**	1.09***
DIS	0.00	0.00*	0.00	4.67**	1.20	0.00***	1.53	0.77	19.99***	0.17	1.40	0.00**	1.22	1.00	2.29	0.00	0.00***	0.00***
COE*DIS	**1.31***	**1.42***	**2.78***	**0.99**	**1.00**	**1.02**	**1.01**	**1.04**	**0.92****	**1.07**	**1.01**	**1.49****	**1.01**	**1.02**	**0.97**	**1.60**	**5.53*****	**3.47*****
MBV	1.40***	1.66***	1.97**	1.15	1.28**	1.43*	1.11**	1.30***	1.28*	1.00	1.03	0.89***	1.03	1.01	0.80	1.01	1.09	0.90
DIS	1.69	1.11	2.34	3.83***	1.02	0.00***	1.97***	2.92***	4.41***	1.81*	1.46	3.03*	1.69***	1.51	0.76	948.51	0.00***	0.00***
MBV*DIS	**2.09***	**0.80**	**0.59**	**0.70**	**0.54**	**5 36*****	**0.93**	**0.43*****	**0.66**	**0.74**	**1.79**	**0.08****	**1.01**	**1.09**	**2.09****	**0.01**	**0.00*****	**0.00*****
SIZE	0.86**	0.80	0.74	1.02	1.01	1.07	0.93***	0.86***	0.93	1.29***	1.28***	1.33**	0.86***	0.76***	0.81	1.01	0.90	0.70
DIS	0.00*	0.00	0.22	67.71	389.32	0.00***	0.19*	0.38	18.98	36.67	1919 91	53.76	0.01*	0.02	0.33	1.01	0.00***	6.36
SIZE*DIS	**1.95****	**1.44**	**1.08**	**0.87**	**0.74**	**1 85*****	**1.12****	**1.08**	**0.92**	**0.86**	**0.72**	**0.87**	**1.27****	**1.23**	**1.06**	**0 56**	**0.00*****	**0.01**
AMV	1.12	1.77**	1.13	1.31*	0.96	0.40*	1.13*	1.45***	1.69***	1.12	1.32*	1.17	0.92	1.23	0.86	2.43***	2.10*	2.01
DIS	4.95***	1.63	3.47	3.26***	0.56	0.00***	2.02***	1.96**	7.31***	2.39**	4.67***	6.45**	1.38*	1.67	0.73	6 91***	151.77**	37.38*
AMV*DIS	**0.80**	**0.67**	**0.44**	**1.17**	**1.96**	**4 51*****	**0.94**	**0.96**	**0.51***	**0.79**	**0.53****	**0.56**	**1.28***	**0.94**	**1.59**	**0.46***	**0.00****	**0.21****

Note This table presents the regression results for each SEO type during economic disruptions (Model 2) It displays the interactions (in bold) of the *DIS* variable with each independent variable as a separate regression, holding all other independent variables constant (a total of 10 independent regressions) The models were executed in this way to prevent the potential for multicollinearity of the *DIS* variable with other instances of *DIS* within the same regression The results have been consolidated into one single table (above) and the standard errors have been included in the Appendices to avoid overcrowding in the table A relative risk ratio (RRR) less than 1 indicates that a firm was more likely to experience less-than-normal volatility, an RRR coefficient of 1 (or close to 1) indicates that the independent variable had no effect on a firm's abnormal return volatility and an RRR coefficient greater than 1 denotes that a firm was more likely to experience abnormal return volatility Abnormal return volatility (*AVAR–GARCH*) is further classified into three categories, denoting its level: category 1 (low abnormal return volatility), category 2 (moderate abnormal return volatility) and category 3 (high abnormal return volatility) ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively

6.5 Robustness Test Results

To ensure the robustness of the findings, multiple specifications and proxies were applied to Models 1 and 2 for each SEO type. First, both models were re-estimated for each SEO type under an alternate specification 'vce(cluster)', which allows intragroup correlation by relaxing the requirement that each observation must be independent (Cameron & Miller 2015). This involved allowing clustering in the standard errors for each of the 31-day event windows. This specification was also used because it corrects any potential correlation of observations within the 31-day event window. Appendix 2.1 presents the results of Models 1 and 2 under this specification, and it is confirmed that the results are largely unchanged. The second robustness test applied was the replacement of the dependant variable in the model with an alternate measure for abnormal return volatility, to ensure that the independent variables it was regressed against remained statistically significant. Specifically, *AVAR–GARCH* was substituted with the *AVAR–GJR–GARCH* measure that captures the leverage effect within the abnormal return volatility proxy. The results in Appendix 2.2 confirm the robustness of the dependant variable because the statistical significance of each independent variable remained unchanged. The third, and final, robustness test employed was the replacement of independent variables that were consistently statistically significant, namely, abnormal trading volume and stock illiquidity. Abnormal trading volume (*AVOL*) was substituted with abnormal turnover ratio (*ATR*) and Amihud's (2002) illiquidity ratio was substituted with Goyenko, Holden and Trzcinka's (2009) Amivest liquidity ratio (*LIQ*). The results reported in Appendix 2.3 confirm that the statistical significance of each variable remain largely unchanged, and thus, the original results are robust to change in the variable measurement. Moreover, the RRR coefficients for *LIQ* were less than 1 but the RRR coefficients for the *ILLIQ* variable from the original regression were greater than 1. This is because the *ILLIQ* variable measures the degree of stock illiquidity, whereas *LIQ* measures the degree of stock liquidity, and therefore, an increasing

RRR coefficient for *ILLIQ* is equivalent to a lower RRR for *LIQ*. The statistical significance for *LIQ* remains consistent with *ILLIQ*, which confirms the robustness of the variable.

6.6 Implications of the Results

To understand the implication of these results on firms and their shareholders, this section uses the regression results from Table 6.5 (entire sample period) and Table 6.6 (economic disruptions) to create a framework (see Table 6.8) for supporting the SEO decision-making process, which will ultimately help firms to choose an SEO type according to its ability to reduce the abnormal return volatility impact on shareholders. The analysis of each SEO type reveals that some independent variables instigate higher levels of abnormal return volatility (at various levels) in particular SEO types than do others. Using these new insights, firms should work towards choosing an SEO type whereby the changes in the independent variables either have no effect on abnormal return volatility or, in a best-case scenario, reduce it. This thesis acknowledges that each firm has its own unique set of financial circumstances that may affect its ability to follow the ideal choices set out in Table 6.8. Thus, this framework merely operates as a tool to support a firm’s SEO decision.

In this framework, each SEO type is assigned a ranking between 1 and 6. A ranking of 1 means that that the SEO type has the *lowest probability* of experiencing abnormal return volatility and therefore merits high consideration from firms. This lowest probability is measured by having the largest percentage of statistically significant independent variables reducing return volatility (RRR < 1) or having no effect (RRR = 1) relative to the total number of statistically significant independent variables. In contrast, a ranking of 6 suggests that the SEO type has the *highest probability* of experiencing abnormal return volatility and therefore should be avoided by firms. This SEO type is measured as the type consisting of the largest percentage of statistically significant independent variables that instigate abnormal levels of return volatility

(RRR > 1 consisting of 3 categories) relative to the total number of statistically significant independent variables. Using the regression results from Tables 6.5 and 6.6, Table 6.7 provides an example that explains the process by which each SEO type was assigned a ranking. The example was undertaken for placement & SPP during the entire sample period, with a calculated value of 38%. This indicates that 38% of the statistically significant independent variables were responsible for either reducing return volatility or had no effect on return volatility. In this case, an SEO type with a higher percentage suggests that there is a greater probability of a firm to experience lower levels of return volatility, which is more ideal and is therefore ranked higher.

Table 6.7: Example of the SEO Type Ranking Process

	Placement & SPP (Entire Sample Period)					
Category	**1**	**2**	**3**	**Variable with an RRR < 1 or approx. 1?**	**Variable with an RRR > 1?**	**Total**
Independent Variable	**RRR**	**RRR**	**RRR**			
AVOL	1.48***	1.61***	1.76***	×	✓	
DISC	1.18***	1.23***	1.43***	×	✓	
ILLIQ	1.01***	1.01***	1.02***	✓	×	
BAS	1.03	1.06	0.93	N/A	N/A	
MSA	1.03***	1.04***	1.03	×	✓	
CIT	0.85	1.76	0.64	N/A	N/A	
COE	1.00	0.97*	0.97	✓	×	
MBV	1.03	1.02	0.86	N/A	N/A	
SIZE	0.89***	0.78***	0.82	✓	×	
DIS	1.70***	1.59*	1.10	×	✓	
AMV	1.11*	1.16*	1.23	×	✓	
Constant	0.52	3.68	0.20	N/A	N/A	
Total number of statistically significant variables				**3**	**5**	**8**
Total number of statistically significant independent variables with RRR < 1 or approx. 1 as a percentage of the total number of statistically significant independent variables				**38%**		

Note. N/A indicates that the independent variable in question did not produce any statistically significant RRR coefficient across any category.

This ranking was applied to each SEO type in Tables 6.5 and 6.6 to subsequently produce Table 6.8. Panel A of Table 6.8 shows the ranking of each SEO type during the entire sample period, which will be useful for firms to rely on during most economic periods. Placement & SPP is noted to be the most ideal SEO type since it has the highest percentage (38%) of independent variables that fall into the 'low or no volatility' category, relative to the 'abnormal return volatility' category. In contrast, the placement & renounceable rights issue is ranked as the least ideal SEO choice because it has the lowest percentage (17%) of independent variables that fall into the 'low or no volatility' category, relative to the 'abnormal return volatility' category. The ranking of SEO types in between placement & SPP and placement & renounceable rights issue follows the same process, and firms can choose the types at their own discretion. Panel B in Table 6.8 highlights the ideal SEO choices for firms during economic disruptions, suggesting that private placements are the most ideal choice, whereas standalone non-renounceable rights issues are the least ideal. These rankings highlight that the SEO types that firms may choose during normal economic periods may not be the most ideal to use during economic disruptions. For example, placement & SPP is ranked the highest during the entire sample period but the second lowest during economic disruptions. This finding highlights the importance of firms to remain flexible in choosing an SEO type during different economic periods, rather than consistently using a single type. Last, it should be noted that this framework is only a guide and recommends an ideal SEO type based on abnormal return volatility. This thesis acknowledges that many other firm-level internal factors may affect a firm's SEO decision, such as profitability, existing capital structure and capital requirements. Firms ultimately need to decide for themselves according to their individual circumstances about whether a high-ranking SEO type will be a good fit for their corporate structure and their shareholders.

Table 6.8: Ideal SEO Choices

Panel A: Ideal SEO Choices During the Entire Sample Period										
SEO Type	**Number of Statistically Significant Independent Variables in Each Category**									
	Low or No Volatility			**Abnormal Return Volatility**						
	(1)	(2)	(1) + (2)	(3)	(4)	(5)	(3) + (4) + (5)	(1) + (2) / Total of (1) to (5)	
	Category 0 (*RRR < 1, less-than-normal return volatility*)	No effect (*RRR of approx. 1*)	Total	Category 1 (*RRR > 1, Low AVAR–GARCH*)	Category 2 (*RRR > 1, Moderate AVAR–GARCH*)	Category 3 (*RRR > 1, High AVAR–GARCH*)	Total	Probability of experiencing *low* volatility (%)	Risk Level
Placement & SPP	1	2	3	0	3	2	5	38	1
Non-renounceable rights issue	0	2	2	2	0	2	4	33	2
Placement	1	2	3	2	2	3	7	30	3
Placement & non-renounceable rights issue	1	1	2	1	0	5	6	25	4
Renounceable rights issue	2	0	2	2	2	2	6	25	5
Placement & renounceable rights issue	0	1	1	2	1	2	5	17	6

Note. This table summarises the ideal choices that firms should consider when choosing an SEO in general (Panel A) as well as during economic disruptions (Panel B). Category 0 (less-than-normal volatility where the RRR < 1) and the no effect category (RRR = 1) are defined as 'low or no volatility'. In contrast, categories 1, 2 and 3 (RRR > 1) are referred to as 'abnormal return volatility'. The second-last column represents the percentage of independent variables that fall into the 'low or no volatility' category (more preferred for firms) relative to the total number of statistically significant variable across all categories. A higher percentage in this column is preferred and therefore is used as the method to determine the most preferrable SEO, which is specified in the last column. Each SEO type is assigned a ranking from 1 (most ideal) to 6 (least ideal). The probabilities attached to each SEO type (second-last column of the table) indicates the probability of experiencing *less-than-normal* or *no volatility*. The percentages range from 0% (i.e. all statistically significant variables instigate abnormal return volatility) to 100% (i.e. all statistically significant variables reduce return volatility). Thus, an SEO type with a higher percentage is more ideal and therefore ranked higher.

Table 6.8: Ideal SEO Choices (Continued)

Panel B: Ideal SEO Choices During Economic Disruptions										
SEO Type	Number of Statistically Significant Independent Variables in each Category									
	Low or No Volatility			Abnormal Return Volatility						
	(1)	(2)	(1) + (2)	(3)	(4)	(5)	(3) + (4) + (5)	(1) + (2) / Total of (1) to (5)	
	Category 0 (*RRR < 1, less-than-normal return volatility*)	No effect (*RRR of approx. 1*)	Total	Category 1 (*RRR > 1, Low AVAR–GARCH*)	Category 2 (*RRR > 1, Moderate AVAR–GARCH*)	Category 3 (*RRR > 1, High AVAR–GARCH*)	Total	Probability of experiencing *low* volatility (%)	Risk Level
Placement	5	0	5	2	0	0	2	71	1
Placement & renounceable rights issue	5	0	5	0	1	2	3	63	2
Placement & non-renounceable rights issue	3	0	3	0	2	2	4	43	3
Renounceable rights issue	3	0	3	3	0	1	4	43	4
Placement & SPP	2	0	2	2	2	2	6	25	5
Non-renounceable rights issue	0	1	1	0	0	6	6	14	6

Note. This table summarises the ideal choices that firms should consider when choosing an SEO in general (Panel A) as well as during economic disruptions (Panel B). Category 0 (less-than-normal volatility where the RRR < 1) and the no effect category (RRR = 1) are defined as 'low or no volatility'. In contrast, categories 1, 2 and 3 (RRR > 1) are referred to as 'abnormal return volatility'. The second-last column represents the percentage of independent variables that fall into the 'low or no volatility' category (more preferred for firms) relative to the total number of statistically significant variable across all categories. A higher percentage in this column is preferred and therefore is used as the method to determine the most preferrable SEO, which is specified in the last column. Each SEO type is assigned a ranking from 1 (most ideal) to 6 (least ideal). The probabilities attached to each SEO type (second-last column of the table) indicates the probability of experiencing *less-than-normal* or *no volatility*. The percentages range from 0% (i.e. all statistically significant variables instigate abnormal return volatility) to 100% (i.e. all statistically significant variables reduce return volatility). Thus, an SEO type with a higher percentage is more ideal and therefore ranked higher.

6.7 Summary

The objective of this chapter was to highlight the presence of abnormal return volatility across various SEO types and to examine their determinants. This was achieved through answering RQ2 and RQ3. To answer these questions, this chapter provided an in-depth discussion of the determinants of abnormal return volatility for each SEO type, across the entire sample period (Model 1) as well as during economic disruptions (Model 2). The first part of the chapter presented a detailed discussion of the descriptive statistics for each SEO type and the trends identified in SEO choices by firms over time. The trend analysis revealed that standalone private placements were the most popular SEO choice prior to 2012. However, after the ASX committed to strengthening Australia's equity capital markets in 2012 through increasing retail shareholder participation, the popularity of combined SEOs grew. This trend has continued and is still prominent today.

The second half of the chapter reported the Phase 1 and Phase 2 results for each SEO type. The Phase 1 results showed how the traditional abnormal return volatility proxy (*AVAR*) varies over time for each SEO type with particular attention given to the three economic disruption periods, since they were associated with high abnormal return volatility. Moreover, an analysis of the similarities and differences between the traditional *AVAR* proxy and the improved *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies was also undertaken. The analysis revealed that the improved abnormal return volatility proxies (*AVAR–GARCH* and *AVAR–GJR–GARCH*) were more accurate because the traditional *AVAR* proxy tended to overstate the abnormal return volatility of some SEO types but to understate that of others based on the degree of volatility clustering. As highlighted previously, Tsay (1987) asserted that the conditional variance component of the *AVAR–GARCH* proxy uses the previous period's variance to determine the current period's variance, that is, volatility clustering. This makes it a more accurate measure than the standard variance measurement used in the traditional *AVAR* proxy, which assumes that each period's variance is independent. For these reasons, the improved abnormal return volatility proxies were employed as the dependant variable in Phase 2.

In Phase 2, MLRs were undertaken for each SEO type to understand their determinants across the entire sample period as well as during economic disruptions. The results confirmed the importance of examining each SEO type separately rather than the aggregate market since each SEO type experienced varying levels of abnormal return volatility in response to changes in each independent variable. Despite there being key differences between SEO types, some overall trends were also identified. Using the data for the entire sample period, the results revealed that *AVOL*, *MBV*, *DIS* and *AMV* had the most widespread impact on abnormal return volatility across all SEO types, whereas *SIZE* was the largest contributor to the reduction in return volatility. In contrast, during economic disruptions, *MSA*, *COE* and *SIZE* played a larger role in eliciting abnormal return volatility across most SEO types, whereas *AVOL* and *CIT* were the largest contributors to the reduction in return volatility. Robustness tests were also conducted; the results confirmed that the outcome was largely unchanged. The chapter concluded with a discussion on the implications of the results, which ranked each SEO type from the lowest to the highest probability of experiencing abnormal return volatility. SEO types with a lower probability were ranked higher, whereas those associated with a higher probability were ranked lower. These rankings were based on the number of statistically significant independent variables that instigated either less-than-normal or no return volatility relative to the total number of statistically significant independent variables. During the entire sample period, the most ideal SEO type was placement & SPP and the least ideal was placement & renounceable rights issue. During economic disruptions, private placements were the most ideal, whereas non-renounceable rights issues were the least ideal. The fact that the abnormal return volatility varied for each SEO across the entire sample period relative to economic disruptions, highlight the importance of firms remaining flexible in choosing an SEO type, rather than sticking to a single type.

The next chapter address RQ4 and RQ5 of this thesis by providing a thorough discussion of the determinants of abnormal return volatility during SEO announcements in each Australian sector. This will involve an analysis of the Phase 1 and Phase 2 results, followed by a discussion of the implication of the findings on a firm's SEO decisions.

Chapter 7: Abnormal Return Volatility and Its Determinants across Australian Sectors

7.1 Introduction

This chapter provides a comprehensive discussion of the regression results of each Australian sector from the econometric models specified in Chapter 4. In this chapter, RQ4 and RQ5 are addressed and are specified as follows:

RQ4: Which Australian sectors exhibit abnormal return volatility in response to SEO announcements and is this exacerbated during economic disruptions?

RQ5: What are the determinants of the abnormal return volatility found across each Australian sector?

Section 7.2 presents the descriptive statistics for each ASX sector over the sample period. Following this, section 7.3 and 7.4 explains and analyses the Phase 1 and Phase 2 results for each sector. Under section 7.3, the Phase 1 results discuss the changes in behaviour of abnormal return volatility (proxied by the traditional *AVAR* measure) in each sector over the study period, with special attention given to economic disruptions. Further, a comparison is also provided of the abnormal return volatility values produced in Phase 1 by the traditional *AVAR* proxy relative to those produced by the improved *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies, which provides justification for their use as the dependant variables in Phase 2. In Section 7.4, the Phase 2 results are presented, which discusses the results of the MLR modelling undertaken to understand the determinants of abnormal return volatility for firms issuing SEOs in each sector, across the entire sample period (Model 1) and during economic disruptions (Model 2).

Section 7.5 explains the robustness test results ensure that the regression results are reliable. The chapter concludes with section 7.6 discussing the implications of the results on the SEO choices for firms within each sector.

7.2 Descriptive Statistics

Table 7.1 presents the descriptive statistics for the dependant and independent variables in each sector. On comparing the abnormal return volatility for each sector, the largest mean value for the traditional *AVAR* proxy is observed in the Financials sector (1.45), but the largest variability (standard deviation) is there in the Consumer Staples sector (6.23). In contrast, the lowest mean value for the traditional *AVAR* proxy is for the Materials sector (0.968), and this sector is also the only one to experience less-than-normal volatility (*AVAR* < 1). In contrast to the traditional *AVAR* proxy, the improved *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies produced values below 1 in all sectors, indicating that all experience less-than-normal volatility. These statistics highlight that the traditional *AVAR* proxy tends to overstate abnormal return volatility levels because it does not incorporate volatility clustering (Tsay 1987).

For the Consumer Staples sector, the largest mean values were for *AVOL*, *DISC*, *BAS* and *CIT*. The literature has highlighted that a large mean value for these variables are associated with larger negative effects on shareholder portfolios (Certo, Holmes & Holcomb 2003; Ching, Firth & Rui 2006; Dierkens 1991; Shahzad et al. 2014; Sony & Bhaduri 2021). For the Financials sector, the largest mean values were for *SIZE* and *AMV* and *DIS*. The large value for *SIZE* is consistent with the fact that five of the 10 largest stocks (by market capitalisation) listed on the ASX 200 Index (i.e. the data utilised in this thesis) are in the Financials sector (i.e. Commonwealth Bank of Australia, National Australia Bank, Westpac Banking Corporation, Australia and New Zealand Banking Group and Macquarie Group). Other notable statistics include the Information Technology sector having the highest mean values for *ILLIQ*, indicating that this sector is likely to consist of investors who trade in the same direction, which increases stock illiquidity but also can lead to higher returns (Chebbi, Ammer & Hameed 2021; Nguyen 2010). Other general findings include the mean value for *COE* being the largest for the Consumer Discretionary sector, the mean value for *MBV* being the largest for the Health Care sector and the mean value for *MSA* during SEOs being the largest for the Energy sector.

Skewness and kurtosis tests were administered to ascertain whether the variables are normally distributed or not. As expected, the variables are not normally distributed. The kurtosis values for the abnormal return volatility proxies (*AVAR*, *AVAR–GARCH* and *AVAR–GJR–GARCH*) and *AVOL* were large across all sectors. This indicates that the data distribution is heavy tailed relative to a normal distribution, which is deemed higher risk, but is nonetheless an inherent feature of financial asset data (Brennan & Subrahmanyam 1996). Moreover, Alberg, Shialit and Yousef (2008) asserted that heavy tails are a sign of volatility clustering and leptokurtosis (observations that are clustered together, resulting in the peak/kurtosis to be substantially higher than a normal distribution) and are also commonly observed in financial asset data. *ILLIQ* also carries a relatively large kurtosis across most sectors. This is because during economic disruptions, the risk of stock illiquidity increases significantly, resulting in a fatter tail distribution, relative to the low levels of stock illiquidity during normal economic periods (Fry 2018). Furthermore, the abnormal return volatility proxies (*AVAR*, *AVAR–GARCH* and *AVAR–GJR–GARCH*) exhibit a high positive skewness. Similarly to the high values observed for each SEO type as discussed in Chapter 6, the high skewness in each sector arises because most of the abnormal return volatility values are closer to 0, with spikes in these variables only occurring closer to the event day. Figure 7.1 shows the spikes in abnormal return volatility (*AVAR–GARCH* presented as an example) that typically occur during the [−3, +3] period of the entire 31-day SEO event window. Notably, the MLR assumptions do not require normality, and therefore, high skewness and kurtosis values will not affect the ability of the regression to produce reliable results.

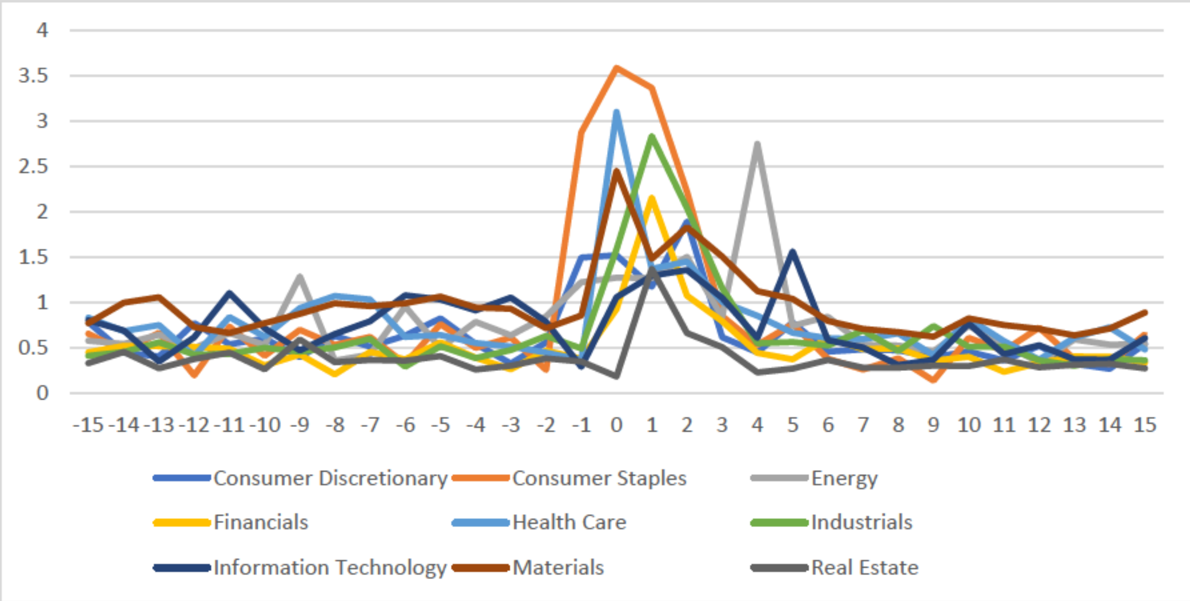


Figure 7.1: Average Daily *AVAR–GARCH* for Each Australian Sector during the SEO Event Window

Note. This figure captures the average abnormal return volatility for each day during the event window, for each of the ASX sectors across the entire sample period.

Table 7.1: Descriptive Statistics for Each Sector

	Consumer Discretionary					**Consumer Staples**					**Energy**					**Financials**					**Health Care**				
Variables	**M**	**SD**	**Skewness**	**Kurtosis**	**Obs.**	**M**	**SD**	**Skewness**	**Kurtosis**	**Obs.**	**M**	**SD**	**Skewness**	**Kurtosis**	**Obs.**	**M**	**SD**	**Skewness**	**Kurtosis**	**Obs.**	**M**	**SD**	**Skewness**	**Kurtosis**	**Obs.**
AVAR	1 15	3.49	11.35	186.60	1,984	1.40	6.24	12.52	187.95	620	1.24	4.05	11.65	185.23	1,054	1.45	4.55	12.74	258.98	2,387	1.10	2.76	7.87	96.01	1,333
AVAR–GARCH	0.65	1.74	8.47	105.40	1,984	0.84	3.01	8.17	78.86	620	0.79	2.28	11.08	196.68	1,054	0.52	1.25	5.74	48.32	2,387	0.80	1.90	9.09	149.94	1,333
AVAR–GJR–GARCH	0.65	1.74	8.47	105.66	1,984	0.84	3.01	8.16	78.54	620	0.79	2.29	11.15	198.79	1,054	0.52	1.25	5.73	48.08	2,387	0.80	1.91	9.00	147.12	1,333
AVOL	1.64	3.95	14.31	282.00	1,984	1.66	2.18	5.67	48.88	620	1.54	2.00	6.16	61.89	1,054	1.47	2.60	19.78	545.82	2,387	1.57	2.50	7.43	92.69	1,333
DISC	0 34	1.59	5.33	29.59	1,984	0.61	2.31	4.06	17.67	620	0.46	1.44	3.73	14.96	1,054	0.16	0.46	4.03	20.27	2,387	0.26	1.48	6.24	40.27	1,333
ILLIQ	0.07	0.45	12.25	185 30	1,984	0.01	0.04	5.25	34.55	620	0.12	0.53	7.23	69.61	1,054	0.04	0.19	10.49	144.28	2,387	0.20	0.46	4.02	26.54	1,333
BAS	-2.88	1.35	0.37	2.46	1,984	-2.46	1.36	0.63	3.48	620	-3.69	1.53	1.24	4.82	1,054	-2.52	1.32	0.69	4.49	2,387	-3.51	1.62	0.32	2.79	1,333
MSA	6.63	4.41	1.27	3.70	1,984	4.85	2.48	0.51	2.39	620	20.88	10.41	0.47	2.84	1,054	8.60	5.78	1.66	6.20	2,387	6.93	5.29	2.40	10.97	1,333
CIT	0.02	0.15	6.19	39.36	1,984	0.04	0.19	4.90	25.00	620	0.02	0.15	6.55	43.85	1,054	0.03	0.18	5 29	29.03	2,387	0.03	0.16	6.12	38.42	1,333
COE	0 28	0.26	7.27	57.10	1,984	0.27	0.11	0.08	3.41	620	0.27	0.09	0.73	3.79	1,054	0.28	0.06	2.88	21.40	2,387	0.19	0.09	-0.59	2.79	1,333
MBV	1 17	0.87	-1.25	7.50	1,984	0.69	0.48	0.66	3.04	620	0.55	0.68	0.65	3.24	1,054	0.71	0.78	0 31	3.07	2,387	1.60	0.98	0.32	2.61	1,333
SIZE	20.73	1.19	-0.97	4.04	1,984	21.02	1.17	2.08	8.28	620	21.03	2.03	-0.59	2.71	1,054	22.30	1.83	-0.61	3.32	2,387	19.90	1.87	0.11	1.97	1,333
DIS	0.09	0.29	2.78	8.71	1,984	0.14	0.35	2.03	5.13	620	0.06	0.24	3.75	15.06	1,054	0.19	0.39	1 58	3.50	2,387	0.12	0.32	2.39	6.73	1,333
AMV	0.73	0.68	1.92	8.33	1,984	0.77	0.90	3.71	24.80	620	0.65	0.59	1.88	8.28	1,054	0.89	0.97	2.72	13.79	2,387	0.76	0.81	3.33	21.82	1,333

	Industrials					**Information Technology**					**Materials**					**Real Estate**				
Variables	**M**	**SD**	**Skewness**	**Kurtosis**	**Obs.**	**M**	**SD**	**Skewness**	**Kurtosis**	**Obs.**	**M**	**SD**	**Skewness**	**Kurtosis**	**Obs.**	**M**	**SD**	**Skewness**	**Kurtosis**	**Obs.**
AVAR	1 15	3.99	12.79	218 28	1,891	1.01	2.47	6.49	57.63	899	0.97	3.73	22.54	718.38	4,247	1.11	2.91	17.47	514.70	2,914
AVAR–GARCH	0.67	2.27	12.11	195 12	1,891	0.75	1.69	8.83	144.40	899	0.97	2.33	7.87	98.84	4,247	0.38	1.05	13.79	341.03	2,914
AVAR–GJR–GARCH	0.67	2.27	12.11	195 13	1,891	0.75	1.69	8.78	143.09	899	0.97	2.33	7.80	97.24	4,247	0.38	1.05	13.73	337.83	2,914
AVOL	1.44	2.38	13.34	268.78	1,891	1.32	1.39	3.63	25.44	899	1.52	2.52	16.57	462.57	4,247	1.36	1.78	17.78	570.46	2,914
DISC	0 18	0.88	7.57	58.49	1,891	0.06	0.14	2.86	13.17	899	0.53	1.74	10.92	124.53	4,247	0.54	1.52	6 53	44.07	2,914
ILLIQ	0.03	0.15	10.35	144.01	1,891	0.22	0.80	5.20	35.79	899	0.11	0.41	7.37	71.95	4,247	0.03	0.14	11.27	162.68	2,914
BAS	-3.17	1.47	0.39	3.77	1,891	-3.11	1.62	0.36	2.80	899	-3.65	1.39	0.71	3.97	4,247	-3.49	1.25	-0.20	5.69	2,914
MSA	11.57	8.27	1.65	6.01	1,891	7.69	4.33	0.41	2.11	899	11.93	7.79	1.03	3.89	4,247	9.98	4.36	1 16	5.53	2,914
CIT	0.03	0.16	6.04	37.42	1,891	0.02	0.16	6.16	38.89	899	0.02	0.14	6.90	48.58	4,247	0.02	0.15	6 17	39.07	2,914
COE	0 26	0.10	0.02	3.67	1,891	0.11	0.08	0.32	1.61	899	0.27	0.13	0.40	4.83	4,247	0.28	0.04	1.60	7.14	2,914
MBV	0.71	0.98	0.39	3.03	1,891	1.50	1.42	-1.32	5.62	899	0.92	1.09	1.03	5.07	4,247	0.23	0.71	1.89	7.86	2,914
SIZE	21.43	1.37	-0.61	3.26	1,891	19.95	2.34	-0.71	2.91	899	19.97	1.94	-0.40	2.71	4,247	21.38	1.05	0 14	2.84	2,914
DIS	0 13	0.34	2.19	5.78	1,891	0.14	0.34	2.11	5.47	899	0.10	0.30	2.73	8.47	4,247	0.08	0.27	3 17	11.03	2,914
AMV	0.77	0.75	2.83	20.44	1,891	0.73	0.98	5.28	44.03	899	0.78	0.73	2.10	10.32	4,247	0.70	0.66	2.47	15.17	2,914

Note. *AVAR* is the traditional abnormal return volatility proxy and is calculated as the average of the squared abnormal returns for the event window divided by the variance of returns during the estimation window; *AVAR–GARCH* and *AVAR–GJR–GARCH* are the improved abnormal return volatility proxies, measured as the average of the squared abnormal returns for the event window divided by the conditional forecasted variance during the estimation window The calculation of the conditional variance in the *AVAR–GJR–GARCH* proxy also accounts for the leverage effect within the conditional variance component; *AVOL* is the abnormal trading volume, calculated as the daily trading volume during the SEO event window divided by the average trading volume during the estimation window; *DISC* refers to the SEO discount, which is calculated as the difference between the SEO offer price and the closing share price, divided by the closing share price; *ILLIQ* is the stock illiquidity, which is the natural logarithm of 1 plus the absolute value returns divided by trading volume (in dollars); *BAS* is the bid–ask spread which is calculated as the natural log of the difference between the ask price and the bid price; *MSA* refers to the number of market-sensitive announcements disclosed; *CIT* refers to corporate insider trading, which is a dummy variable carrying the value of 1 if corporate insiders engage in trading behaviour during the event window, or 0 otherwise; *COE* is the cost of equity capital, which is calculated as the square root of 1 divided by the PE growth ratio; *MBV* indicates the market-to-book value and is measured as the natural logarithm of the firm's market capitalisation divided by the book value; *SIZE* refers to the firm size, which is calculated as the natural logarithm of the share price multiplied by the number of shares outstanding; *DIS* is a dummy variable, which takes the value of 1 if there is an economic disruption period, and 0 otherwise; and *AMV* refers to the aggregate market volatility, which is calculated as the daily conditional variance (using GARCH (1,1) estimations) of the ASX 200 Index

7.3 Phase 1 Results: Measurement and Comparison of Abnormal Return Volatility Proxies across Australian Sectors

The purpose of this section is to understand the impact of SEO announcements on abnormal return volatility across each Australian sector, which will address RQ4. This section also discusses the similarities and differences between the three proxies for abnormal return volatility (*AVAR*, *AVAR–GARCH* and *AVAR–GJR–GARCH*), to verify the higher degree of accuracy that the *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies provide over the traditional *AVAR* proxy.

7.3.1 Hypothesis 2(b)

In this subsection, Hypothesis 2(b) is tested, which compares the abnormal return volatility observed across high-, moderate- and low-performing sectors. As mentioned in Chapter 3, Hypothesis 2(b) is specified as follows:

> H_{2b}: *High- and moderate-performing sectors experience a larger degree of abnormal return volatility than low-performing sectors.*

Table 7.2 presents the results of the average *AVAR* in each sector for each year, with particular attention given to economic periods of disruption. During the dot-com bubble, firms in the Energy and the Health Care (both high-performing) sectors experienced the largest *AVAR* of 5.79 and 2.77, respectively, thus supporting Hypothesis 2(b). The large *AVAR* for the Energy sector is as expected because investors typically show a preference for value-driven investments (i.e. commodities such as crude oil, gold and silver mined/extracted by Energy firms) as a hedge against the rising inflation rates during the onset of the bursting dot-com bubble (Junttila, Pesonen & Raatikainen 2018). Moreover, a large portion of SEOs issued in this sector during this time were private placements, highlighting that institutional shareholders took on this inflation-hedging opportunity by purchasing Energy stocks through private placements (De Gregorio 2012). Apart from the Consumer Staples sector, all other high- and moderate-performing sectors experienced abnormal return volatility during the dot-com bubble, which supports Hypothesis 2(b). Moreover, the fact that the Real Estate (low-performing) sector did not experience abnormal return volatility further validates Hypothesis 2(b).

During the GFC, high-, moderate- and low-performing sectors all experienced abnormal return volatility during SEOs. The fact that the abnormal return volatility of firms in the Real Estate sector also doubled (2.00) despite it being classified as a low-performing sector is contrary to Hypothesis 2(b). Hiang Liow (2012) showed that the excessive volatility in the Australian real estate sector during the 2008 GFC was due to the collapse of the US real estate market, resulting in a contagion impact on the Australian Real Estate sector. As the Australian economy recovered in 2009, the *AVAR* for all sectors dropped to below 1, despite the volume of SEOs being higher than in 2008. This finding highlights the importance of understanding that a higher number of SEO issuances does not always equate to a higher *AVAR*. Rather, the increase in SEO issuances during 2009 (approximately AUD106 billion) coupled with a lower *AVAR* is an indication of increasing stock returns, which will lower *AVAR* (Schwert 1990). Fuelled by a resurgence in investor confidence, the stock market rebounded strongly and yielded higher returns in 2009 after bottoming out in March 2009 (ASX 2010). This was observed across most firms in the ASX 200 Index, in which market wide volatility had fallen back to pre-GFC levels by the end of 2009 (ASX 2010). As an exception, the Materials sector showed a slight increase in the *AVAR* which is likely because the Materials sector is a net receiver of volatility and therefore is more likely to experience volatility when other sectors may not (Mensi et al. 2021).

During the COVID-19 pandemic, all high- and moderate-performing sectors except for Industrials, experienced abnormal return volatility. Of these sectors, the Consumer Staples (7.29), the Consumer Discretionary (4.30), the Health Care (8.27), the Information Technology (2.76) and the Financials (2.20) sectors all experienced higher levels of abnormal return volatility during the COVID-19 pandemic than during the GFC and the dot-com bubble. This implies that shareholders exhibit a greater degree of sensitivity to SEO announcements during a public health-related crises than during a financial crisis. The fact that the abovementioned sectors were most affected by SEOs is not surprising owing to a few reasons. With respect to the Consumer Staples sector, the substantial increase in sales of durable and non-durable goods during 2020 boosted profits in this sector. For example, Wesfarmers, JB Hi-Fi and Domino's Pizza, which are part of this sector, recorded significant improvements in performance because of government-mandated lockdowns, which forced most of the population to work from home and stimulated the consumption of the products sold by these types of firms. The high performance of retail firms during the pandemic enticed many shareholders to participate in SEOs, allowing them to purchase stocks at discounted prices (Hall, MC et al. 2020). This was evident from the AUD36.3 billion in SEOs raised by ASX-listed firms within only 5 months, from March to August 2020 (ASIC 2020a). As mentioned earlier, the only sector that did not experience abnormal return volatility during the COVID-19 pandemic was Industrials, likely because firms in this sector are heavy users of oil, which crashed in price during 2020. This crash allowed these firms to piggyback off the low oil prices and financial government support to produce goods more cheaply and therefore increase their profit margins. Consequently, they were less reliant on SEOs to conduct their operations. The firms that did use SEOs relied on private placements, which was shown in Table 6.8 in Chapter 6 as the SEO type that had the greatest probability of experiencing low volatility during economic disruptions. Consequently, it is not unexpected that despite being a moderate-performing sector, the Industrials sector did not experience abnormal return volatility during the COVID-19 pandemic.

With respect to the Health Care sector, the increase in the *AVAR* is justified by the large injection of capital directed towards medical supplies for treating COVID-19 patients and financial support for vaccine trials (IBISWorld 2020a). However, the uncertainty about the trials and vaccine efficacy (at that time) were likely to be contributors to the heightened uncertainty amongst investors regarding the future performance and viability of these firms, thus contributing to the abnormal return volatility. Regarding the Information Technology sector, during 2020, shareholders continued to inject capital into this sector based on the speculation and growth surrounding buy-now-pay-later services such as Afterpay Ltd and Zip Co Ltd (ASIC 2020b). As the unemployment rate peaked in July 2020, the increased reliance on these services helped individuals cover their purchases, thereby fuelling the profits of these firms (ASIC 2020b). Moreover, as Australia went into lockdown, the forced shift towards using online platforms to conduct daily business operations provided a platform for firms such as Xero, NEXTDC and WiseTech to profit immensely (Gleeson 2020). These factors caused a significant demand for these and speculative trading of these stocks during SEOs, evident from the exponential recovery of the equity market during the second half of 2020. The heightened interest in these types of stocks was a key reason for the increased shareholder participation in SEOs in this sector, which contributed to the abnormal return volatility. Last, the increase in abnormal return volatility within the Financials sector during the COVID-19 pandemic is as expected due to the deteriorating consumer confidence and the increased unemployment rate fuelled by the falling demand for credit by individuals and businesses (IBISWorld 2020b). Despite the fall in interest rates, the low consumer confidence outweighed the low borrowing costs, which negatively affected the performance of lending institutions. This resulted in the shift of existing shareholders and the new wave of retail investors to flock to high-performing sectors, such as Health Care and Information Technology. Last, as in the GFC period, the Real Estate sector experienced abnormal return volatility during the COVID-19 pandemic, which is contrary to Hypothesis 2(b). However, the *AVAR* was the lowest in this sector compared with all other sectors that experienced abnormal return volatility.

In summary, the results highlight that abnormal return volatility was prominent across all high- and moderate-performing sectors and was intensified during economic disruptions, lending support to Hypothesis 2(b). The only exceptions were the Consumer Staples sector during the dot-com bubble and the Industrials sector during the COVID-19 crisis. On average, the Energy and the Health Care sectors were the most sensitive to SEOs, evidenced by higher abnormal return volatility. Contrary to Hypothesis 2(b), the Real Estate sector (classified as a low-performing sector) also experienced abnormal return volatility during two of the three economic disruptions (the GFC and the COVID-19 pandemic). This result implies that firms in these sectors need to consider the effects of their SEO decision on their shareholders because it also has the capacity to affect shareholder confidence, which may affect the firms' ability to raise capital in the future.

Table 7.2: Abnormal Return Volatility (*AVAR*) by Sector

		High-performing Sectors			**Moderate-performing Sectors**					**Low-performing Sector**
Economic Disruption Period	Year	Health Care	Information Technology	Energy	Consumer Discretionary	Consumer Staples	Industrials	Materials	Financials	Real Estate
		AVAR	*AVAR*	*AVAR*	*AVAR*	*AVAR*	*AVAR*	*AVAR*	*AVAR*	*AVAR*
	1999	0.44	1.15	N	N	0.58	0.51	0.98	1.16	1.39
Dot-com bubble	2000	**2.77**	N	**5.79**	0.65	0.85	N	N	0.75	0.69
	2001	0.87	N	0.64	**1.63**	N	N	**1.03**	**1.17**	0.87
	2002	0.84	N	N	N	N	N	0.61	0.56	0.74
	2003	1.18	N	N	N	0.50	0.52	1.06	0.75	0.71
	2004	0.52	N	0.80	0.33	0.64	1.36	1.01	1.07	1.11
	2005	0.89	N	N	0.64	2.46	0.53	1.37	1.11	1.12
	2006	1.54	N	N	1.17	0.89	1.39	0.96	0.88	0.81
	2007	1.08	N	0.80	0.69	N	0.93	1.37	0.81	1.01
GFC	2008	**1.64**	**2.34**	**2.93**	**1.04**	**3.72**	**1.85**	**2.14**	**2.11**	**2.00**
	2009	0.46	0.39	0.49	0.74	0.17	0.35	1.08	0.70	0.85
	2010	N	0.55	0.78	0.71	N	0.57	1.30	0.65	0.93
	2011	0.96	1.39	0.22	1.09	1.35	1.00	0.88	0.70	1.67
	2012	0.80	0.86	1.49	1.64	0.30	1.39	1.70	0.72	1.14
	2013	1.33	0.64	N	1.13	0.90	0.70	0.81	0.53	0.83
	2014	0.74	0.99	0.67	0.93	0.50	0.75	0.63	1.72	0.60
	2015	1.35	0.98	0.59	1.29	0.99	1.26	0.89	1.25	1.58
	2016	0.52	0.87	0.86	0.60	1.39	0.97	0.70	2.18	1.21
	2017	0.65	0.91	0.77	0.50	0.78	0.76	1.63	0.60	0.77
	2018	1.16	1.60	1.06	1.54	0.85	1.42	1.20	1.60	2.39
	2019	0.89	0.91	N	0.75	0.67	0.98	1.02	0.91	0.86
COVID-19 pandemic	2020	**8.27**	**2.76**	**1.92**	**4.30**	**7.29**	0.72	**1.56**	**2.20**	**1.46**

Note. This table presents the results of the average yearly *AVAR* values on a sectoral basis. Firms were classified into 11 sectors according to the Global Industry Classification Standard. The values are interpreted as follows: if the value is below 1, this indicates that firms who chose the given SEO type experienced less-than-normal volatility, a value of 1 indicates that the SEO had no effect on the firm's return volatility and a value above 1 indicates that the SEO instigated an abnormal impact on the firm's return volatility. N indicates that no SEO was issued by firms in the respective sector during the given year. The years during which an economic disruption occurred are highlighted in grey, and the values in bold pertain to the SEO types that experienced abnormal return volatility.

7.3.2 Comparing the Traditional *AVAR* proxy to the Improved *AVAR–GARCH* and *AVAR–GJR–GARCH* Proxies across Each Sector

This subsection compares the traditional *AVAR* proxy to the improved *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies across each sector. The purpose of this comparison is to understand whether the improved proxies reduce or exacerbate the size of abnormal return volatility in each sector. The results for all three proxies for each sector during economic disruptions are summarised in Table 7.3. Similar to the comparisons made for each SEO type in Chapter 6, the interpretation of the various *AVAR* calculations here is similar for each sector. Moreover, since it was established in the previous section that abnormal return volatility was concentrated primarily across the three economic disruptions, the comparisons between the traditional *AVAR* proxy and the improved *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies are undertaken for these three periods.

Table 7.3 shows that the *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies estimate abnormal return volatility more conservatively for some sectors but magnify it for others compared with the traditional *AVAR* proxy. Tsay (1987) highlighted that the conditional variance component of the *AVAR–GARCH* proxy uses the previous period's variance to determine the current period's variance, that is, volatility clustering. This feature makes it more accurate than the standard variance measurement used in the traditional *AVAR* proxy, which assumes that each period's variance is independent (Tsay 1987). Hence, for the sectors that exhibited a higher degree of volatility clustering, the improved proxies estimate the abnormal return volatility to be higher than that estimated by the traditional *AVAR* proxy. The sectors that have higher *AVAR–GARCH* values compared with the traditional *AVAR* proxy values include the Consumer Discretionary sector during the dot-com bubble and the GFC, the Materials sector during the dot-com bubble and the Energy sector during the GFC. Conversely, for the sectors that experienced a lower degree of volatility clustering, the abnormal return volatility was estimated to be lower than that estimated by the traditional *AVAR* proxy. These sectors include all the remaining sectors across all three economic disruptions. A comparison of the two improved *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies with each other does not reveal a substantial difference between their values. Although this finding implies that the leverage effect (captured in the *AVAR–GJR–GARCH* proxy) has a minimal effect on abnormal return volatility, it also confirms the robustness of the *AVAR–GARCH* proxy. A comparison of the three economic disruptions shows that the abnormal return volatility (as measured by *AVAR–GARCH* and *AVAR–GJR–GARCH*) has the largest impact during the COVID-19 pandemic across all sectors except for the Industrials sector. Of these affected sectors, the Health Care, the Consumer Staples and the Consumer Discretionary sectors experienced the highest levels of abnormal return volatility. This is an expected result because as previously mentioned in Section 7.3.1, these sectors experienced a significant increase in performance during 2020, resulting in higher SEO participation rates.

In summary, it is evident that the improved proxies increase the accuracy of the measurement of abnormal return volatility. As highlighted earlier, the improved proxies (*AVAR–GARCH* and *AVAR–GJR–GARCH*) produce more accurate measurements of abnormal return volatility than the traditional *AVAR* proxy. As a result, the improved proxies produce higher abnormal return volatility values for the sectors with a higher degree of volatility clustering, that is, during the dot-com bubble (Consumer Discretionary and Materials) and the GFC (Consumer Discretionary and Energy). All the remaining sectors across the three economic disruption periods produced a lower abnormal return volatility value with the improved *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies than with the traditional *AVAR* measure, indicating that these sectors exhibited a lower degree of volatility clustering. For these reasons, the two improved proxies are used as the dependant variable in the MLR model. The results of these regressions are covered in the following section (i.e. Phase 2). Specifically, *AVAR–GARCH* is used as the dependant variable in the base models and *AVAR–GJR–GARCH* is used as the dependant variable in the robustness tests. The results of these regression are covered in detail in the following section.

Table 7.3: Comparison of *AVAR*, *AVAR–GARCH* and *AVAR–GJR–GARCH* during Economic Disruptions (by Sector)

Economic Disruption Period	**Sector**	**Year**	***AVAR***	***AVAR–GARCH***	***AVAR–GJR–GARCH***
Dot-com bubble	Consumer Discretionary	2000	0.65	0.35	0.35
	Consumer Staples	2000	0.85	0.26	0.26
	Energy	2000	5.79	5.39	5.38
	Financials	2000	0.75	0.40	0.40
	Health Care	2000	2.77	1.28	1.28
	Real Estate	2000	0.69	0.34	0.34
	Consumer Discretionary	2001	1.63	2.79	2.78
	Energy	2001	0.64	0.85	0.85
	Financials	2001	1.17	0.92	0.93
	Health Care	2001	0.87	0.53	0.53
	Materials	2001	1.03	1.73	1.72
	Real Estate	2001	0.87	0.23	0.23
GFC	Consumer Discretionary	2008	1.04	1.52	1.52
	Consumer Staples	2008	3.72	2.21	2.21
	Energy	2008	2.93	4.03	4.02
	Financials	2008	2.11	1.67	1.66
	Health Care	2008	1.64	0.74	0.74
	Industrials	2008	1.85	1.49	1.48
	Information Technology	2008	2.34	0.95	0.96
	Materials	2008	2.14	1.91	1.90
	Real Estate	2008	2.00	1.47	1.46

COVID-19 pandemic	Consumer Discretionary	2020	4.30	1.94	1.95
	Consumer Staples	2020	7.29	1.70	1.70
	Energy	2020	1.92	1.27	1.27
	Financials	2020	2.20	1.31	1.30
	Health Care	2020	8.27	4.16	4.16
	Industrials	2020	0.72	0.56	0.56
	Information Technology	2020	2.76	2.68	2.69
	Materials	2020	1.56	1.12	1.13
	Real Estate	2020	1.46	1.09	1.08

Note. This table presents the comparison of the traditional *AVAR* proxy with the improved *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies. The firms are classified into 11 sectors according to the Global Industry Classification Standard, and three economic periods of disruption are considered (i.e. the dot-com bubble, the GFC and the COVID-19 pandemic). The values are interpreted as follows: if the value is below 1, this indicates that firms who chose the given SEO type experienced less-than-normal volatility, a value of 1 indicates that the SEO had no effect on the firm's return volatility and a value above 1 indicates that the SEO instigated an abnormal impact on the firm's return volatility.

7.4 Phase 2 Results: Determinants of Abnormal Return Volatility across Australian Sectors

This section addresses RQ5 by providing a detailed discussion of the regression results for Phase 2, which examines the determinants and the degree to which they affect abnormal return volatility (using the *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies) for each Australian sector.

7.4.1 Hypothesis 3(b): Abnormal Trading Volume (*AVOL*)

Hypothesis 3(b) posits that an increase in *AVOL* results in a larger increase in abnormal return volatility for firms in high- and moderate-performing sectors, compared to those in low-performing sectors. This effect is due to the causal relationship between *AVOL* and abnormal return volatility in ASX-listed stocks (Shahzad et al. 2014). Regarding its specific impact, high- and moderate-performing sectors are expected to experience increased levels of abnormal return volatility for each unit increase in *AVOL*, compared with low-performing sectors. This is because high- and moderate-performing sectors provide faster growth rates, which entices shareholder participation, resulting in higher trading volume during SEOs and therefore higher volatility (He, Jarnecic & Liu 2016).

Table 7.4 shows that during the entire sample period, firms across all sectors experienced abnormal return volatility for each unit increase in *AVOL*, regardless of its sectoral performance. Interestingly, even the Real Estate sector, which is a low-performing one, experienced moderate levels of abnormal return volatility alongside the Health Care (high-performing) sector. He, Jarnecic and Liu (2016) and T West and Worthington (2006) explained that the Real Estate sector typically experiences the highest trading volume of all sectors in Australia, resulting in an increase in volatility, which is also expected to persist during SEOs. Interestingly, the Financials sector experienced low levels of abnormal return volatility even though it was a moderate-performing sector. Monagle et al. (2006) suggested that the low volatility is attributable to the lower levels of trading volume during SEOs in this sector because of the higher degree of stability of the share price of firms in this sector. Last, all remaining sectors experienced high levels of abnormal return volatility. These results show that the causal relationship between *AVOL* and abnormal return volatility as described by Shahzad et al. (2014) holds true for all sectors, rather than high- and moderate-performing sectors only. According to these findings, Hypothesis 3(b) is rejected for Model 1. Thus, high-, moderate- and low-performing sectors all experience higher levels of abnormal return volatility for each unit increase in *AVOL*.

Table 7.5 highlights that during economic disruptions, the pattern of abnormal return volatility in response to *AVOL* presents mixed results across sectors. Of the high- and moderate-performing sectors, firms in the Energy, the Consumer Discretionary, the Industrials and the Consumer Staples sectors continued to experience either moderate or high levels of abnormal return volatility. However, interestingly, the Health Care and the Materials sectors experienced less-than-normal volatility although both had experienced abnormal levels of volatility according to the Model 1 results, which is contrary to Hypothesis 3(b). The low volatility in the Health Care sector may be because it is a counter-cyclical defensive sector that has greater levels of stability during periods of economic crisis, resulting in lower trading volume and therefore less volatility (Alam, Wei & Wahid 2020; Laborda & Olmo 2021). Moreover, the Materials sector experienced low abnormal return volatility likely because firms in this sector mostly used private placements. Melia, Docherty and Easton (2020) highlighted that the Materials sector is a heavy issuer of private placements during economic disruptions, which is associated with lower abnormal return volatility. Last, the Real Estate sector experienced less-than-normal volatility, which is as expected since it is a low-performing sector. Thus, Hypothesis 3(b) is rejected for Model 2 because contrary to expectations, some high- and moderate-performing sectors (Health Care and Materials) experienced low-than-normal volatility. These findings suggest that just because a firm that operates in a high- or moderate-performing sector experiences abnormal levels of trading volume, it does not automatically mean that it will also experience abnormal return volatility. In fact, these results highlight that regardless of the sector in which a firm operates, if the firm's stock is actively traded and there is a high degree of trading volume (likely because of a high degree of stock liquidity), it helps to reduce the risk of abnormal return volatility (Weber & Rosenow 2006).

7.4.2 Hypothesis 4(b): SEO Discount (*DISC*)

Hypothesis 4(b) states that an increase in *DISC* has a larger effect on abnormal return volatility in high- and moderate-performing sectors compared with that of low-performing sectors. This is because shareholders in high- and moderate-performing sectors tend to be more sensitive to larger discounts, resulting in an increase in return volatility (Altınkılıç & Hansen 2003; Lei & Yucan 2016).

Table 7.4 presents rather mixed results, showing that during the entire sample period, some moderate-performing sectors (Consumer Discretionary and Materials) and low-performing sectors (Real Estate) produced statistically significant RRR coefficients, resulting in the rejection of Hypothesis 4(b) for Model 1. More importantly, the RRR coefficients were all close to 1, indicating that a 1 unit increase in the *DISC* had no effect on abnormal return volatility in any of these sectors across the entire sample period. Interestingly, none of the high-performing sectors had statistically significant RRR coefficients, suggesting that an increase in the SEO discount did increase the risk of a firm experiencing abnormal return volatility. These results are contrary to those of existing research (Altınkılıç & Hansen 2003; Lei & Yucan 2016), which suggests that high-performing firms that issue SEOs at a larger discount will experience higher volatility. These results suggest that offering a larger SEO discount affects firms across all sectors, and therefore, all firms (regardless of their performance) should ensure they do not provide too deep a discount since it can instigate abnormal levels of return volatility and have greater negative effects on their shareholders. This negative volatility impact may ultimately outweigh any potential benefits they receive from the discount, if the discount offered is too large.

In contrast, during economic disruptions (Table 7.5), the Health Care (high-performing), the Financials, the Materials (both moderate-performing) and the Real Estate (low-performing) sectors experienced abnormal return volatility in response to an increase in the *DISC*. Specifically, the Health Care and the Materials sectors experienced high levels of abnormal return volatility and the Financials and the Real Estate sectors experienced moderate levels. Since both high- and low-performing sectors experienced abnormal return volatility during economic disruptions, Hypothesis 4(b) is rejected for Model 2. These findings indicate that shareholders in all sectors, irrespective of firms' performance, express concern if firms offer higher *DISC*s during periods of economic uncertainty (Chan, YC, Saffar & Wei 2021).

Although a deep discount is usually how firms entice investors to partake in the SEO during uncertain times, the results show that it has a larger negative effect on shareholders.

7.4.3 Hypothesis 5(b): Stock Illiquidity (*ILLIQ*)

Hypothesis 5(b) predicts that an increase in *ILLIQ* has a larger effect on abnormal return volatility in higher-performing sectors, compared with that in lower-performing sectors. This expectation is based on the positive relationship between stock illiquidity and return volatility (Amihud & Mendelson 1986; Brennan & Subrahmanyam 1996; Datar, Naik & Radcliffe 1998; Hasbrouck 1993; Ho et al. 2005). More specifically, Nguyen (2010) argued that when there are many sell orders for a share, but an insufficient number of buyers to fill the order, the share price dips at an accelerated rate. This increased selling pressure causes an order imbalance, resulting in the stock illiquidity to increase, which translates into abnormal return volatility. A disproportionately larger number of sell orders occurs in high-performing sectors, because most market participants simultaneously trade in the same direction, compared with low-performing sectors (Chebbi, Ammer & Hameed 2021).

Interestingly, Table 7.4 shows that across the entire sample period, most sectors produced RRR coefficients close to 1, indicating that a 1 unit increase in *ILLIQ* had no effect on a firm's abnormal return volatility, which is contrary to Hypothesis 5(b). The only sectors in which *ILLIQ* affected abnormal return volatility were the Consumer Staples (moderate-performing) and the Real Estate (low-performing) sectors. The results for these two sectors lend support to existing studies that assert that investors react negatively to *ILLIQ* because it induces higher levels of volatility (Amihud & Mendelson 1986; Asem, Chung & Tian 2016; Bams & Honarvar 2021; Qian 2011). However, it is interesting to note that most sectors were unaffected by increases in *ILLIQ*. A likely reason is that shareholders are not as concerned about *ILLIQ* for large-capitalisation (ASX 200 listed) firms since these firms have a lower liquidity risk and any increase in *ILLIQ* will be short-lived (Bilinski, Liu & Strong 2012). Moreover, Eckbo, Masulis and Norli (2000) also argued that the process of issuing an SEO improves a stock's liquidity, thereby reducing the liquidity risk.

In contrast, Table 7.5 reports that the impact of *ILLIQ* during economic disruptions was more widespread across ASX sectors, including Health Care, Information Technology, Energy, Consumer Discretionary, Financials and Industries. This finding is in line with existing research that argues that order imbalances occur in high-performing sectors because shareholders usually trade in the same direction, which increases volatility (Chebbi, Ammer & Hameed 2021; Nguyen 2010). Nevertheless, one unexpected result is that the two sectors (Consumer Staples and Real Estate) previously associated with abnormal return volatility in Model 1 did not produce any statistically significant RRR coefficients during economic disruptions (Model 2). Considering that the abnormal return volatility of firms operating in high- and moderate-performing sectors was more affected by an increase in *ILLIQ*, compared with that of low-performing sectors, Hypothesis 4(b) is accepted for Model 2.

7.4.4 Hypothesis 6(b): Information Asymmetry (*BAS*)

Hypothesis 6(b) states that firms in low-performing sectors will experience a higher level of abnormal return volatility, compared with that of high-performing sectors during periods of increasing information asymmetry (proxied by the bid–ask spread). The basis of this hypothesis is that firms in low-performing sectors tend to have less information disclosures, which can lead to a higher degree of information asymmetry (Cheng, Courtenay & Krishnamurti 2005). This occurs because these sectors are typically in their maturity phase and therefore provide a smaller number of operational updates to their shareholders. Examples of operational updates include the announcements of mandatory quarterly and annual reports. Thus, the reduced number of information disclosures leads investors to feel uninformed about the ongoing business operations (Sejjaaka 2007). Thus, the higher information asymmetry, which manifests in lower investor confidence, leads to the higher risk of firms experiencing abnormal return volatility.

Table 7.4 shows that across the entire sample period. information asymmetry affects abnormal return volatility across high-, moderate- and low-performing sectors, rather than in low-performing sectors only. As expected in Hypothesis 6(a), the highest levels of abnormal return volatility were experienced by firms in the Real Estate (low-performing) sector, which experiences a high degree of information asymmetry. Moreover, the Energy (high-performing) and the Materials (moderate-performing) sectors produced RRR coefficients of less than 1, signalling that firms in these sectors were more likely to experience less-than-normal volatility. These findings are in line with those of existing research, which posits that in the presence of information asymmetry, low-(higher) performing firms will experience higher (lower) abnormal return volatility (Cheng, Courtenay & Krishnamurti 2005; Sejjaaka 2007). Contrary to expectations, some high- and moderate-performing sectors (Health Care, Consumer Discretionary and Financials) also experienced high abnormal return volatility. Fosu et al. (2016) suggested that it is also possible for information asymmetry to instigate abnormal return volatility in high-performing firms if they are sensitive to periods of economic uncertainty. In this case, the Health Care and the Consumer Discretionary sectors were affected by the COVID-19 pandemic because of the increased pressure on the health system and the excessive demand for household durable goods, respectively. During this period of uncertainty, firms that did not provide the continuous disclosure of information during an SEO announcement were more likely to be penalised by investors, resulting in high levels of abnormal return volatility. A similar argument can also be made for the Financials sector, which was likely affected by the GFC in 2008. Thus, Hypothesis 6(b) is rejected because in addition to low-performing sectors, various high- and moderate-performing sectors also experienced abnormal return volatility.

Table 7.5 shows the impact of information asymmetry on abnormal return volatility for each sector during economic disruptions. Interestingly, the results show that an increase in information asymmetry during economic disruptions did not induce abnormal return volatility in any sector. In fact, the Energy (high-performing) and the Consumer Discretionary (moderate-performing) sectors elicited less-than-normal volatility. All the remaining sectors did not produce statistically significant coefficients for this variable. This may be beneficial for firms in these two sectors that are planning to issue an SEO during periods of high information asymmetry throughout economic disruptions. Following these findings, Hypothesis 6(b) is also rejected for Model 2, highlighting that an increase in information asymmetry does not tend to induce abnormal levels of return volatility during economic disruptions.

7.4.5 Hypothesis 7(b): Market-sensitive Announcements (*MSA*)

Hypothesis 7(b) posits that low-performing sectors experience higher abnormal return volatility than high-performing sectors, in response to market-sensitive announcements. This is because firms in the former sectors are less likely to meet their continuous disclosure obligations, resulting in a lower number of market-sensitive announcements (Seamer 2014; North 2011). Thus, when firms in these sectors disclose information, it is usually only ‘material’ market-sensitive disclosures, which elicit a larger shareholder reaction (Brown, Kwan & Wee 2006). Thus, it is expected that if low-performing sectors release these ‘material’ disclosures within the 6 months leading up to an SEO announcement, it instigates higher levels of abnormal return volatility compared with that of high-performing sectors that release these material disclosures more often.

Table 7.4 shows that during the entire sample period, firms in the Health Care (high-performing), the Materials (moderate-performing) and the Real Estate (low-performing) sectors all experienced abnormal return volatility in response to *MSA*. As anticipated, the Real Estate sector, as the only low-performing sector, produced the highest RRR coefficient in category 3, indicating that firms in this sector experienced high levels of abnormal return volatility. In contrast, the Health Care (high-performing) and the Materials (moderate-performing) sectors generated low and moderate levels of abnormal return volatility, respectively. Consistent with the findings of Brown, Kwan and Wee (2006), Seamer (2014) and North (2011), this thesis shows that low-performing sectors are indeed more affected by *MSA* than are high-performing sectors, which provides support to Hypothesis 7(b). Unexpectedly, the Energy (high-performing) and the Consumer Staples (moderate-performing) sectors produced RRR coefficients below 1, indicating that firms in these sectors experienced less-than-normal volatility in response to *MSA*. The low volatility in the Consumer Staples sector may be because this sector had one of the lowest number of market-sensitive announcements compared with all other ASX sectors (Fernández 2012). With respect to the Energy sector, although this sector had the largest number of market-sensitive announcements, these were primarily scheduled progress report announcements, which do not induce return volatility in this sector for they are more consistent in nature and are expected by market participants (Fernández 2012; Prasad, Bakry & Varua 2020).

In Table 7.5, the results for Model 2 (economic disruptions) are similar to those for Model 1, whereby *MSA* continued to induce abnormal return volatility in the Health Care, the Materials and the Real Estate sectors. Nevertheless, these sectors appeared to experience higher levels of abnormal return volatility during economic disruptions (Model 2) than they did during the entire sample period (Model 1). In this case, the Health Care sector moved from low (in Table 7.4: Model 1) to moderate (in Table 7.5: Model 2) levels of abnormal return volatility, and the

Materials sectors moved from moderate (in Model 1) to high (in Model 2) levels of abnormal return volatility. Surprisingly, the abnormal return volatility for firms in the Real Estate sector (low-performing) changed from high levels in Model 1 to moderate levels in Model 2. In contrast, the Information Technology and the Industrials sectors experienced less-than-normal volatility during economic disruptions, despite being high- and moderate-performing sectors, respectively. These results highlight that *MSA* in Models 1 and 2 affected each sector differently with no observable trend. This may because there are 19 types of market-sensitive announcements issued by ASX-listed firms, each of which is likely to instigate varied levels of volatility depending on the type of announcement that is issued more often by firms in each sector (Fernández 2012).

7.4.6 Hypothesis 8(b): Corporate Insider Trading Behaviour (*CIT*)

The effect of corporate insider trading was also mixed across high-, moderate- and low-performing sectors. Hypothesis 8(b) predicts that corporate insider trading results in higher abnormal return volatility for firms operating in higher-performing sectors than for those in lower-performing sectors. This is because corporate insiders engage in selling activity prior to an SEO to capitalise on the price run-up leading up to the SEO (Clarke, Dunbar & Kahle 2001; Gombola, Lee & Liu 1999). The insider trading activity is expected to be higher for firms in high-performing sectors because they experience larger price increases leading up to the SEO announcement compared with firms in low-performing sectors (Huang, Uchida & Zha 2016).

Table 7.4 highlights that across the entire sample, corporate insider trading affects firms in not only high-performing sectors but also moderate- and low-performing sectors. This shows that regardless of the performance of a particular sector, shareholders react to any level of corporate insider trading activity. Although no sectors experienced high levels of abnormal return volatility, the Health Care, the Consumer Discretionary, the Materials and the Real Estate sectors did experience moderate levels and the Financials sectors experienced low levels of abnormal return volatility. Last, the Information Technology, the Energy and the Consumer Staples sectors all experienced less-than-normal volatility. These results however are contrary to those of existing research (Clarke, Dunbar & Kahle 2001; Gombola, Lee & Liu 1999; Huang, Uchida & Zha 2016). Gangopadhyay, Yook and Shin (2014) suggested that the volatility reaction to corporate insider trading activity is usually localised at the firm level. By assuming that corporate insider trading for firms in similar performance sectors (high, moderate or low) will elicit a similar shareholder reaction, may not be useful in identifying a clear trend. They highlighted that instead, when corporate insiders buy shares, shareholders view it positively and therefore also engage in buying activity, regardless of sector performance. In addition, although corporate insider *buying* behaviour causes an increase in volatility, corporate insider *selling* behaviour elicits a higher level of volatility. This suggests that firms in the Health Care, the Consumer Discretionary, the Materials, the Real Estate and the Financials sectors experienced more corporate insider *selling* because of the higher levels of abnormal return volatility experienced. In contrast, corporate insiders in the Information Technology, the Energy and the Consumer Staples sectors likely had a net *buying* position, resulting in lower volatility, which is consistent with the findings of Cline et al. (2014) and Hable (2021). Since there are mixed results observed between high-, moderate- and low-performing sectors, Hypothesis 8(b) is rejected for Model 1, and it can be concluded that the performance of a sector will not be directly affected by corporate insider trading.

In contrast, Table 7.5 shows that corporate insider trading during economic disruptions (Model 2) instigated the highest levels of abnormal return volatility only in the Information Technology and the Real Estate sectors. Interestingly, all other sectors that experienced abnormal return volatility in Model 1 experienced less-than-normal volatility in Model 2. The results show that when corporate insiders in the Information Technology and the Real Estate sectors engaged in trading activity during economic disruptions, shareholders perceived this as a signal and copied the buying or selling behaviour (Chen, GM, Firth & Rui 2001; Wang, J 1994). The fact that the Information Technology sector transitioned from less-than-normal volatility in Model 1 to high abnormal return volatility in Model 2, shows that shareholders were highly reactive to *CIT* in this sector during periods of economic uncertainty. This may be because this sector has witnessed exponential growth rates since 2000, but shareholders are also aware that it tends to experience large losses and high volatility during economic uncertainty (Huynh, Nguyen & Dao 2021). Thus, shareholders closely follow the behaviour of corporate insiders during economic disruptions as a guide. Consequently, Hypothesis 8(b) is rejected for both Models 1 and 2, and it can be concluded that the abnormal return volatility due to *CIT* occurs not only in high-performing sectors, but also in low-performing sectors.

7.4.7 Hypothesis 9(b) – Cost of Equity Capital (*COE*)

Hypothesis 9(b) posits that an increase in COE results in higher and moderately (lower) abnormal return volatility for higher- and moderate- (lower-) performing sectors. This relationship is expected because in high- and moderate-performing sectors, shareholders accept a greater level of risk when participating in SEOs, which leads to a higher *COE* and thus higher volatility. In contrast, in low-performing sectors shareholders do not expect a high degree of risk; thus, firms will incur a lower *COE* and lower volatility (Verrecchia 1999).

Table 7.4 shows that for each unit increase in the *COE*, firms in high- (Energy), moderate- (Financials) and low-performing (Real Estate) sectors experienced abnormal return volatility. Of these sectors, Energy experienced the highest levels of abnormal return volatility, whereas Financials and Real Estate experienced moderate levels. Since firms in high- and low-performing sectors issuing SEOs experienced abnormal return volatility, Hypothesis 9(b) is rejected for Model 1. In contrast, Table 7.5 shows that the Financials sector continued to experience abnormal return volatility during economic disruptions; however, it increased to the highest level of abnormal return volatility. This may be because banking and financial firms are among the most negatively affected during economic disruptions, and thus incur the highest cost of equity for they are considered the highest risk (Demirgüç-Kunt, Pedraza & Ruiz-Ortega 2021). Last, the Information Technology, the Materials and the Consumer Discretionary sectors had RRR coefficients below 1 in Model 1 but experienced abnormal return volatility during economic disruptions. Since high- and moderate-performing sectors were affected by an increase in the *COE* during economic disruptions, Hypothesis 9(b) is accepted for Model 2.

7.4.8 Hypothesis 10(b): Market-to-Book Value (*MBV*)

Hypothesis 10(b) predicts that an increase in the MBV has a larger effect on abnormal return volatility for firms in high-performing sectors, compared with those in low-performing sectors. This relationship is expected because a high *MBV* is typically associated with firms in high-performing sectors that deliver high returns and therefore will experience higher volatility (DeAngelo, DeAngelo & Stulz 2010; Fama & French 1995).

Table 7.4 shows that during the entire sample period, firms in the high- and moderate-performing sectors (Health Care, Information Technology and Industrials) experienced abnormal return volatility for each unit increase in *MBV*. Specifically, the high-performing sectors (Health Care and Information Technology) experienced higher levels of abnormal return volatility, whereas moderate-performing sectors (Industrials) experienced low abnormal return volatility. In contrast, the Real Estate (low-performing) sector produced an RRR coefficient of less than 1, indicating that firms in this sector experienced less-than-normal volatility. These results are consistent with existing studies, which showed that high-performing sectors consist of firms with high *MBV*s and are more likely to experience abnormal return volatility (DeAngelo, DeAngelo & Stulz 2010; Fama & French 1995), Thus, Hypothesis

10(b) is accepted, which confirms that across the entire sample period, an increase in the *MBV* instigated higher abnormal return volatility in high-performing sectors compared with that of low-performing sectors.

During economic disruptions (Table 7.5), for each unit increase in the *MBV*, firms in the Industrials (moderate-performing) and the Real Estate (low-performing) sectors experienced abnormal levels of return volatility, but firms in the Energy (high-performing) and the Consumer Staples (moderate-performing) sectors experienced less-than-normal volatility. This indicates that during periods of economic uncertainty, an increase in *MBV* will result in abnormal return volatility that is experienced by firms in low-performing sectors. This indicates that the share price of these firms in low-performing sectors is likely increasing during economic disruptions, which is a sign of financial resilience that is viewed more favourably by shareholders, resulting in an increase in shareholder interest during SEOs. Thus, Hypothesis 10(b) is rejected for Model 2, and it can be concluded that an increase in the *MBV* during economic disruptions instigates abnormal return volatility in high-, moderate- and low-performing sectors, rather than in high-performing sectors only.

7.4.9 Hypothesis 11(c): Firm Size (*SIZE*)

Hypothesis 11(c) posits that larger firms in high- and moderate-performing sectors experience higher abnormal return volatility, compared with larger firms in low-performing sectors. This relationship is expected because if large firms (lower risk) issue an SEO in a high-performing sector (with higher returns), this would be an attractive opportunity for shareholders, which will increase SEO participation rates and therefore translate into higher levels of return volatility (Reinganum & Smith 1983).

Table 7.4 shows that this relationship is found in some high- and moderate-performing sectors, including Energy, Materials and Consumer Staples. Mensi et al. (2013) asserted that the

Energy, the Materials and the Consumer Staples sectors have volatility linkages because they are all commodity-based sectors and therefore transmit volatility among each other. The fact that *SIZE* was statistically significant across these sectors confirms that these volatility linkages are stronger among larger firms in these sectors during SEO announcements. In contrast, despite the Financials and the Industrials sectors also being moderate-performing sectors, they experienced less-than-normal volatility during SEO announcements. Therefore, although this finding does support the well-documented negative association between firm size and return volatility (Banz 1981; Drew 2003; Reinganum 1981), it does not concur with Hypothesis 11(c). This suggests that only large firms in moderate-performing sectors, which have volatility linkages (i.e. Energy, Materials and Consumer Staples), will experience abnormal return volatility, whereas all other larger firms across other sectors will not, even if they are high-performing sectors (i.e. Health Care and Information Technology).

Interestingly, these volatility linkages were not observed for economic disruptions (see Table 7.5). Instead, only the Health Care (high-performing) and the Industrials (moderate-performing) sectors experienced abnormal return volatility for each unit increase in *SIZE*, but at the lowest level (category 1). This indicates that larger firms in these two sectors were more reliant on SEOs during economic disruptions. This may be because the Health Care sector is counter-cyclical and the Industrials sector is more resilient during economic uncertainty, and therefore, firms in these sectors have a higher chance of raising capital through an SEO (Alam, Wei & Wahid 2020; Laborda & Olmo 2021; Szczygielski et al. 2022). The fact that high- and moderate-performing sectors experienced abnormal return volatility, whereas low-performing sectors did not, confirms that during SEOs *SIZE* does play a larger role in inducing abnormal return volatility for firms in high-performing sectors, compared with low-performing sectors. From these results, Hypothesis 11(c) is accepted for both Models 1 and 2.

7.4.10 Hypothesis 12(b): Aggregate Market Volatility (*AMV*)

Hypothesis 12(b) predicts that an increase in *AMV* will have a similar effect on abnormal return volatility in firms across all sectors (Sharma, Narayan & Zheng 2014). This is because aggregate market volatility tends to affect the overall sentiment of the market, which transmits volatility across all sectors. As shown in Table 7.4, apart from the Materials sector, all sectors did indeed experience abnormal return volatility across the entire sample period. The reason that the Materials sector did not experience abnormal return volatility in response to an increase in *AMV* is because firms in this sector were heavy issuers of private placements, which constitute institutional shareholder participation. Consequently, an increase in *AMV* (driven mainly by retail shareholders) was unlikely to deter institutional shareholders from participating in SEOs undertaken by these firms because they have a higher risk tolerance (Melia, Docherty & Easton 2020). Across all other sectors that were affected by *AMV*, moderate levels of abnormal return volatility were experienced. This is in line with the findings of Sharma, Narayan and Zheng (2014), who argued that an increase in *AMV* leads to higher levels of return volatility within all firms regardless of the sector that they operate in. In addition, Information Technology was the only sector to experience high levels of abnormal return volatility. Z Wang (2010) asserted that this sector has remained quite sensitive to aggregate market changes over time, causing firms in this sector to experience higher levels of volatility than firms in other sectors.

Table 7.5 highlights that during economic disruptions, Health Care was the only sector to continue experiencing abnormal return volatility. These results are contrary to that of Campbell et al. (2001), who argued that the impact of *AMV* increases during economic disruptions. In fact, firms in the Financials, the Consumer Staples and the Real Estate sectors experienced less-than-normal volatility. This suggests that these sectors do not need to be concerned about issuing SEOs during volatile periods amid an economic disruption. In line with these results, Hypothesis 12(b) is accepted for Model 1 and rejected for Model 2.

Table 7.4: Summary of Regression Results for Each Sector (Entire Sample Period – Model 1)

	High-performing Sectors								
	Health Care			Information Technology			Energy		
Category	1	2	3	1	2	3	1	2	3
Variable	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR
AVOL	1.33***	1.41***	1.37***	1.59***	1.87***	1.94***	1.33***	1.43***	1.65***
DISC	0.99	0.96	1.02	1.01	1.02	1.02	1.00	1.00	0.98
ILLIQ	1.02***	1.02***	1.02***	1.01***	1.01***	1.02***	1.01**	1.01**	1.01*
BAS	1.19**	1.17	0.77	0.87	0.85	1.20	0.84*	1.00	0.48**
MSA	1.05***	0.98	1.06	1.04	0.99	0.73	0.99	1.01	0.89**
CIT	1.41	5.78**	0.00***	0.76	0.00***	0.00***	0.62	0.00***	0.00***
COE	0.99	1.00	0.98	0.97*	0.98	0.94	1.02	0.98	1.14**
MBV	0.98	1.56**	0.87	1.52***	1.61***	2.89***	1.03	1.30	0.39
SIZE	1.03	0.88	0.95	1.08	1.14	0.64	0.94	0.69***	1.81*
DIS	1.25	0.72	4.67	0.89	0.48	0.90	1.67	2.91**	2.52
AMV	1.08	1.51**	0.78	1.34**	1.25	1.65***	1.08	1.58*	1.38
Constant	0.05*	0.15	0.01	0.00**	0.00**	20.38	0.11	53.86	0.00**

	Moderate-performing Sectors															**Low-performing Sector**		
	Consumer Discretionary			Financials			Industrials			Materials			Consumer Staples			Real Estate		
Category	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Variable	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR
AVOL	1.08	1.12*	1.13*	1.26*	1.35	1.36	1.22*	1.27*	1.36**	1.26***	1.40***	1.48***	1.19**	1.31*	2.21***	1.36***	1.52***	1.48***
DISC	1.00	0.96***	1.00	0.94	1.08	0.19	0.99	0.50	0.22	1.01	1.00	1.01*	0.90	1.07	1.11	1.01	0.99*	0.95
ILLIQ	1.02***	1.02***	1.02***	1.00	1.00	1.01*	1.02***	1.01	1.02**	1.02***	1.02***	1.03***	1.17***	1.15**	1.21***	1.06***	1.06***	1.06***
BAS	0.94	1.21*	1.38*	0.99	1.26**	1.04	0.90	0.92	1.21	0.86***	0.86**	0.78***	0.90	1.11	0.74	1.10	1.05	1.61*
MSA	1.00	0.96	0.92	1.00	0.97	1.03	1.00	0.98	1.02	1.01**	1.03***	1.02	1.01	0.71*	0.51**	0.99	0.95	1.15**
CIT	1.15	4.15**	2.69	2.31**	1.65	0.00***	1.17	1.25	1.30	1.81**	1.54	1.89	1.86	0.00***	0.00***	1.16	4.88**	0.00***
COE	0.99	0.98***	0.99	1.03	1.06*	1.01	1.00	0.99	0.95	0.99***	0.98***	1.02	1.01	1.01	0.91*	1.08***	1.19***	1.06
MBV	1.07	1.18	1.14	1.22	1.55	1.16	1.24**	1.08	0.98	0.97	0.99	1.15	1.15	0.40	4.21	0.75	1.22	0.19***
SIZE	1.09	1.04	1.08	0.89**	0.91	0.80	0.79**	0.77	0.52**	1.23***	1.21***	1.25***	1.06	0.65	7.07***	1.00	1.34	0.58
DIS	1.35	1.02	0.00***	2.80***	2.84**	2.67	5.42***	4.43***	4.96**	1.39*	0.93	1.21	1.25	1.45	0.86	2.40***	1.66	0.00***
AMV	1.13	1.83***	1.23	1.11	1.29**	1.06	1.05	1.40**	1.23	1.09	1.10	0.99	1.13	1.35**	0.72	0.94	1.36**	1.29
Constant	0.02**	0.02	0.00	0.29	0.02	0.39	7.10	3.55	2.52	0.00***	0.00***	0.00***	0.01	574.17	0.00***	0.01**	0.00***	25.28

Note. This table provides the regression results for each sector across the entire sample period (Model 1). It displays the relative risk ratios (RRR) of each variable for each *AVAR–GARCH* category. An RRR coefficient of less than 1 indicates that a firm was more likely to experience less-than-normal volatility, an RRR coefficient of 1 (or close to 1) shows that the independent variable had no effect on a firm's abnormal return volatility and an RRR coefficient greater than 1 denotes that a firm was more likely to experience abnormal return volatility. The abnormal return volatility (*AVAR–GARCH*) is classified into three categories: category 1 (low abnormal return volatility), 2 (moderate abnormal return volatility) and 3 (high abnormal return volatility). The standard errors have been included in the Appendices. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 7.5: Summary of Regression Results for Each Sector (Economic Disruptions – Model 2)

	High-performing Sectors								
	Health Care			Information Technology			Energy		
Category	1	2	3	1	2	3	1	2	3
Variable	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR
AVOL	1.44***	1.54***	1.53***	1.62***	1.86***	1.93***	1.34**	1.43***	1.55***
DIS	2.64***	1.56	14.28**	1.16	0.35	0.84	2.61	3.49	0.02**
AVOL*DIS	**0.69*** **	**0.71*** **	**0.65*** **	**0.83**	**1.11**	**1.01**	**0.82**	**0.95**	**3.72*** **
DISC	0.99	0.97	1.02	1.02	1.04**	1.01	1.00	1.00	0.98
DIS	2.77**	1.82	0.69	1.29	1.88	0.32	2.28*	2.19	2.86
DISC*DIS	**0.00* **	**0.00* **	**4.95* **	**0.98**	**0.92** **	**1.08**	**0.90**	**1.07**	**0.94**
ILLIQ	1.02***	1.02***	1.02***	1.01***	1.01***	1.02***	1.01**	1.01**	1.01*
DIS	1.10	0.51	0.48	0.56	0.31	0.26	1.10	0.89	2.41
ILLIQ*DIS	**1.45**	**2.39** **	**7.40*** **	**69.19** **	**66.16** **	**932.52** **	**1.03** **	**1.05*** **	**0.99**
BAS	1.18**	1.10	0.75	0.83	0.91	1.26	0.87	1.07	0.43**
DIS	1.40	1.55	5.82	1.11	0.22	0.69	0.30	0.48	19.61
BAS*DIS	**1.07**	**1.59**	**1.10**	**1.24**	**0.59**	**0.83**	**0.68**	**0.66* **	**1.55**
MSA	1.04**	0.97	1.06	1.06	1.04	0.75	0.99	1.01	0.89**
DIS	0.52	0.29	8.60	1.58	2.74	2.13	19.63	0.25	31.51
MSA*DIS	**1.18* **	**1.21* **	**0.84**	**0.92**	**0.76*** **	**0.83**	**0.88**	**1.13**	**0.87**
CIT	1.23	6.34**	0.00***	0.70	0.00***	0.00***	0.62	0.00***	0.00***
DIS	1.22	0.78	4.68	0.88	0.48	0.90	1.67	2.91**	2.52
CIT*DIS	**2.08**	**0.00*** **	**1.41**	**1.39**	**0.22**	**26.81* **	**1.00**	**1.00**	**1.00**
COE	0.99	1.00	0.98	0.95***	1.00	0.95	1.02	0.98	1.15**
DIS	0.49	0.07	2.67	0.37*	3.44	244.24***	8.32	0.30	616.80
COE*DIS	**1.04**	**1.11**	**1.03**	**1.11*** **	**0.31**	**0.00*** **	**0.95**	**1.07**	**0.84**
MBV	1.01	1.63**	0.89	1.54***	1.67***	2.96***	1.07	1.28	0.39
DIS	1.79	3.01	7.54	1.10	3.24	2.06	5.92**	2.44	0.46
MBV*DIS	**0.77**	**0.34**	**0.70**	**0.91**	**0.37**	**0.63**	**0.00* **	**1.63**	**1460.84**
SIZE	1.00	0.86	1.05	1.07	1.14	0.65	0.93	0.70***	1.78*
DIS	0.00*	0.00	3.13	38.82	91.36	97.86	0.04	212.58	0.00
SIZE*DIS	**1.48* **	**1.43**	**0.01**	**0.69**	**0.58**	**0.81**	**1.21**	**0.80**	**1.37**
AMV	1.01	1.02	1.03	0.98	0.77	1.02	1.10	1.53	1.28
DIS	1.08	0.30	14.58**	0.63	0.28	0.54	1.76	2.40	1.82
AMV*DIS	**1.12**	**1.82* **	**0.16*** **	**1.50**	**1.87**	**1.78**	**0.93**	**1.25**	**1.42**

Note. This table presents the regression results for each sector during economic disruptions (Model 2). It displays the interactions (in bold) of the *DIS* variable with each independent variable as a separate regression, holding all other independent variables constant (a total of 10 independent regressions). The models were executed in this way to prevent the potential for multicollinearity of the *DIS* variable with other instances of *DIS* within the same regression. The results have been consolidated into one single table (above) and the standard errors have been included in the Appendices to avoid overcrowding in the table. A relative risk ratio (RRR) less than 1 indicates that a firm was more likely to experience less-than-normal volatility, an RRR coefficient of 1 (or close to 1) indicates that the independent variable had no effect on a firm's abnormal return volatility and an RRR coefficient greater than 1 denotes that a firm was more likely to experience abnormal return volatility. Abnormal return volatility (*AVAR–GARCH*) is further classified into three categories, denoting its level: category 1 (low abnormal return volatility), category 2 (moderate abnormal return volatility) and category 3 (high abnormal return volatility). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 7.5 Summary of Regression Results for Each Sector (Economic Disruptions – Model 2) (Continued)

	Moderate-performing Sectors															Low-performing Sector		
	Consumer Discretionary			Financials			Industrials			Materials			Consumer Staples			Real Estate		
Category	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Variable	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR
AVOL	1.07	1.10*	1.12*	1.24	1.31	1.31	1.18	1.24*	1.31**	1.35***	1.58***	1.70***	1.18**	1.30*	1.99***	1.40***	1.55***	1.51***
DIS	1.01	0.71	0.00***	2.50**	2.03	1.22	2.53**	3.24*	0.36	2.20***	2.09**	3.45***	0.96	1.34	0.00**	3.32***	1.69	0.00***
AVOL*DIS	1.18*	1.20*	0.99	1.07	1.18	1.36	1.77**	1.31	3.38***	0.76***	0.67***	0.66***	1.20	1.08	13.91**	0.85	0.96	0.62***
DISC	1.00	0.96***	1.00	0.83	0.84	0.19	0.99	0.28	0.14	1.01	1.00	1.01*	0.90	1.07	1.11	1.01	0.99*	0.95
DIS	1.76*	0.56	0.00***	1.80**	1.30	2.54	5.67***	2.19	2.56	1.22	0.96	0.80	2.19	1.61	1.04	1.48	1.51	0.00***
DISC*DIS	0.02	204.60	0.02	40.04***	246.14**	1.45	0.74	73.37	80.51	1.60	0.79	3.92**	0.00	0.34	0.10	384.02*	4.06	0.11
ILLIQ	1.02***	1.02***	1.02***	1.00	1.00	1.01*	1.02***	1.01	1.02**	1.02***	1.02***	1.03***	1.18***	1.14**	1.22***	1.06***	1.06***	1.06***
DIS	0.92	0.31*	0.00***	2.30***	2.41**	2.41	5.24***	3.28**	4.60**	1.30	0.77	1.30	1.43	1.27	0.95	2.28***	1.69	0.00***
ILLIQ*DIS	2.48***	7.70***	1.60*	4.96**	3.75	2.36	1.18	2.06*	1.49	1.00	1.01	1.00	0.93	1.04	0.93	1.06	0.96	0.95
BAS	0.94	1.21*	1.38*	1.01	1.40***	1.18	0.92	0.98	1.28	0.85***	0.87**	0.77***	0.87	0.96	0.56	1.04	1.21	1.61*
DIS	1.26	1.02	0.00***	2.48**	1.82	1.21	4.41***	1.79	2.60	1.70*	0.50	1.78	1.73	5.70	4.33	5.41***	0.16	0.00***
BAS*DIS	0.98	1.00	0.70**	0.94	0.78	0.68	0.91	0.69	0.74	1.07	0.84	1.12	1.14	1.68	1.81	1.33	0.47	0.79
MSA	1.00	0.95	0.92	0.99	0.97	1.01	1.00	1.00	1.05	1.01*	1.03***	1.02	1.01	0.72*	0.48*	1.00	0.90**	1.15**
DIS	1.79	0.42	0.00***	2.17**	2.58	0.91	5.50***	33.15***	116.30***	0.89	0.51	0.54	1.25	1.93	0.36	2.58*	0.17	0.00***
MSA*DIS	0.94	1.20	1.11	1.04	1.01	1.15	1.00	0.82**	0.71**	1.09**	1.13	1.17*	1.00	0.87	1.36	0.99	1.35***	0.93
CIT	1.25	3.23*	2.66	2.22*	2.11	0.00***	1.18	1.93	3.59	1.85**	1.77	1.32	1.34	0.00***	0.00***	1.55	7.27***	0.00***
DIS	1.38	0.88	0.00***	2.77***	2.95**	2.67	5.42***	4.64***	5.82***	1.40*	0.97	1.12	1.11	1.43	0.84	2.50***	1.89	0.00***
CIT*DIS	0.00***	6.21	0.50	1.09	0.56	0.04***	0.96	0.45	0.00***	0.86	0.00***	4.13	7.77	4.01	71.74	0.00***	0.14	58.22***
COE	0.99	0.98***	0.99	1.01	1.03	0.98	1.01	0.99	1.00	0.98***	0.98***	1.02*	1.00	1.01	0.95	1.07***	1.22***	1.06
DIS	0.39	33.43	0.00***	0.08*	0.02*	0.00**	10.86***	4.86	58.64**	0.83	1.01	3.27	0.21	2.18	9.16	0.23	14.59	0.00***
COE*DIS	1.06	0.84	1.06*	1.12**	1.18**	1.25***	0.97	1.00	0.87*	1.02*	1.00	0.97	1.08	0.98	0.88	1.09	0.72	0.96
MBV	1.07	1.21	1.14	1.28*	1.54	1.25	1.09	1.08	1.07	0.97	1.03	1.08	1.22	0.48	31.38**	0.77	1.32	0.19***
DIS	1.34	1.37	0.00***	3.11***	2.81**	3.23	3.35***	4.30**	7.13***	1.40*	0.95	1.08	1.48	2.67	207.82***	2.17***	1.12	0.00***
MBV*DIS	1.00	0.76	0.65	0.80	1.00	0.66	1.77***	1.02	0.39	1.00	0.65	1.69	0.83	0.51	0.00***	0.43	0.16	9.95**
SIZE	1.11	1.06	1.09	0.85***	0.85	0.77*	0.79**	0.76	0.52**	1.22***	1.21***	1.23***	0.99	0.65	6.72***	0.96	1.35	0.58
DIS	1.31*	5.07	0.00	0.04	0.02	0.06	0.00	162.89	474.52	0.33	0.93	0.13	0.00	0.22	0.00	0.00	3.09	0.00
SIZE*DIS	0.38*	0.54	0.82	1.21	1.24	1.18	1.57*	0.62	0.60	1.07	1.00	1.12	1.51	1.09	2.44	1.34	0.97	1.19
AMV	1.20	2.13***	1.26	1.00	1.79***	1.92**	1.21	1.72**	1.01	1.09	1.14	0.98	1.65**	0.70	1.04	0.98	1.78***	1.32
DIS	1.74*	1.98	0.00***	2.45***	5.12***	12.79***	7.34***	6.68***	3.64	1.36	1.10	1.17	2.32	0.80	1.54	2.64***	3.35*	0.00***
AMV*DIS	0.80	0.64	0.78	1.13	0.64**	0.25***	0.75	0.71	1.32	1.02	0.86	1.04	0.54**	2.08	0.45	0.90	0.57*	0.73

Note. This table presents the regression results for each sector during economic disruptions (Model 2). It displays the interactions (in bold) of the *DIS* variable with each independent variable as a separate regression, holding all other independent variables constant (a total of 10 independent regressions). The models were executed in this way to prevent the potential for multicollinearity of the *DIS* variable with other instances of *DIS* within the same regression. The results have been consolidated into one single table (above) and the standard errors have been included in the Appendices to avoid overcrowding in the table. A relative risk ratio (RRR) less than 1 indicates that a firm was more likely to experience less-than-normal volatility, an RRR coefficient of 1 (or close to 1) indicates that the independent variable had no effect on a firm's abnormal return volatility and an RRR coefficient greater than 1 denotes that a firm was more likely to experience abnormal return volatility. Abnormal return volatility (*AVAR–GARCH*) is further classified into three categories, denoting its level: category 1 (low abnormal return volatility), category 2 (moderate abnormal return volatility) and category 3 (high abnormal return volatility). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

7.5 Robustness Test Results

To ensure the robustness of the findings, multiple specifications and proxies were applied to Models 1 and 2 for each sector. First, both models were re-estimated under an alternate specification ‘vce(cluster)’, which allows intragroup correlation by relaxing the requirement for each observation to be independent (Cameron & Miller 2015). In the context of this thesis, it involved allowing clustering in the standard errors for each 31-day event window. This specification was also used because it corrects any potential correlation of observations within the 31-day event window. Appendix 3.1 presents the results of Models 1 and 2 under this specification, which confirms that the results are largely unchanged. The second robustness test applied was the replacement of the dependant variable in the model with the alternate abnormal return volatility proxy, to ensure that the regression coefficients remain statistically significant. Specifically, *AVAR–GARCH* was substituted with *AVAR–GJR–GARCH*, a measure that captures the leverage effect within the abnormal return volatility proxy. The results in Appendix 3.2 confirm the robustness of the dependant variable because the statistical significance of each independent variable remains unchanged. The third robustness test employed was the use of alternate proxies for independent variables that were consistently statistically significant across most sectors, that is, abnormal trading volume and stock illiquidity. Abnormal trading volume (*AVOL*) was substituted with abnormal turnover ratio (*ATR*) and Amihud’s (2002) illiquidity ratio was substituted with the Amivest liquidity ratio (*LIQ*) (Goyenko, Holden & Trzcinka 2009). The results reported in Appendix 2.3 confirm that the statistical significance of each variable remains largely unchanged; thus, the original results are robust to change in the variable measurement. It should be noted that the RRR coefficients for *LIQ* were less than 1 but the RRR coefficients for *ILLIQ* were greater than 1. This is because *ILLIQ* measures the degree of stock illiquidity, whereas *LIQ* measures the degree of stock liquidity, and thus, a higher RRR for *ILLIQ* is equivalent to a lower RRR for *LIQ*. The statistical significance for *LIQ* remains consistent with that for *ILLIQ*, which confirms the robustness of the variable.

7.6 Implication of the Results

7.6.1 Understanding Risk Levels across Sectors

This section covers the implications of the results for SEO-issuing firms across each ASX sector. To understand the implication of these results on firms and their shareholders, this section uses the regression results from Table 7.4 (entire sample period) and Table 7.5 (economic disruptions) to create the risk scorecard shown in Table 7.6, in order to help firms across various sectors understand their risk of experiencing abnormal return volatility when issuing an SEO. This scorecard acts as a guide for high-risk sectors to be more cautious of their SEO decisions and therefore actively choose low-risk SEO types (as described in Table 6.8 in Chapter 6).

In this framework, each sector is assigned a ranking between 1 and 9. A ranking of 1 means that that the sector has the *lowest probability* of experiencing abnormal return volatility, and therefore, firms in this sector need not be overly cautious about their SEO decisions. The lowest probability of experiencing abnormal return volatility is measured by having the largest percentage of statistically significant independent variables that reduces return volatility (RRR < 1) or has no effect (RRR = 1) relative to the total number of statistically significant independent variables. In contrast, a ranking of 9 suggests that that the SEO type has the *highest probability* of experiencing abnormal return volatility, and therefore, firms should actively monitor their SEO choices to ensure they choose an SEO type that helps to reduce abnormal return volatility. A sector possessing the highest probability of experiencing abnormal return volatility is measured as the sector with the largest percentage of statistically significant independent variables instigating abnormal levels of return volatility (RRR > 1 consisting of three categories) relative to the total number of statistically significant independent variables. An example of the process used to assign risk rankings is provided in Chapter 6, Table 6.7. This ranking was also applied to each sector in Tables 7.4 and 7.5 to subsequently produce Table 7.6.

A comparison of each sector in Table 7.6 reveals that across the entire sample period (Panel A), the Health Care (high-performing) sector has the highest risk of experiencing abnormal return volatility during SEO announcements. The Real Estate (low-performing), the Industrials (moderate-performing) and the Financials (moderate-performing) sectors followed closely behind. Interestingly, the risk rating for these sectors, as the riskiest sectors from a mixture of high-, moderate- and low-performing sectors, is not directly influenced by their performance ratings. In contrast, the lowest-risk sectors across the entire sample period include the Information Technology (high-performing), the Consumer Discretionary and the Consumer Staples (both moderate-performing) sectors. These results highlight that high- (low-) performing sectors are not necessarily considered higher (lower) risk. During economic disruptions (Panel B), the Health Care and the Industrials sectors continued to remain among the riskiest sectors. However, it is particularly interesting to find that the Real Estate sector becomes classified as a low-risk sector. Moreover, the Information Technology sector, which was classified as the lowest-risk sector during the entire sample period, was considered the riskiest sector during economic disruptions. This finding suggests that the risk rating for each sector can change significantly during economic disruptions and that riskier sectors should be explored in greater detail to help firms improve their SEO choices.

7.6.2 Comparing Riskiest Sectors to Ideal SEO Types

To help firms across the highest-risk sectors improve their SEO choices, the SEO types chosen by the firms in these sectors during the entire sample period and economic disruptions was assessed. This assessment will help these firms understand whether there is any room for improvement in their SEO decisions. The three riskiest sectors have been discussed because it is these sectors that need the most guidance on re-assessing their SEO decisions to ensure that they choose an SEO type that reduces their abnormal return volatility impact on shareholders. In contrast, low-risk sectors do not need to be as cautious of their SEO choices since they already appear to be choosing the appropriate SEO types, and thus, an assessment of their SEO choices is unlikely to provide much value to them or their shareholders. To undertake this assessment, the SEO types chosen by each sector are reported in Table 7.7. The SEO choices of the three riskiest sectors shown in Table 7.6 during the sample period (Health Care, Industrials and Real Estate) and economic disruptions (Information Technology, Industrials and Health Care) to understand which SEO types were chosen by these sectors, are then compared against the ideal SEO types highlighted in Chapter 6 – Table 6.8 to determine whether the SEO choices of firms in these sectors can be improved. The results of this comparison for the entire sample period and for economic disruption periods are reported in Table 7.8.

It is apparent that all three high-risk sectors (Health Care, Industrials and Real Estate) were heavy issuers of private placements across the entire sample period (Panel A). However, according to Table 7.8, placement & SPP would have been a more ideal SEO type to choose from the perspective of abnormal return volatility. Specifically, firms in the Health Care sector chose to use this SEO type 10 times over the period, but this choice was overshadowed by private placements because more than double (22 times) the number of firms used that SEO type instead. A similar case existed for the Industrials sector, with private placements being the most popular. Moreover, renounceable rights issue was the second most widely used SEO type, but ranked among the lowest, which is not ideal for firms in the Industrials sector. The Real Estate sector did well by relying mostly on placement & SPP, using it 24 times. Nevertheless, private placements were chosen almost the same number of times (21 times) as placement & SPP. A comparison of these three sectors reveals that the SEO choices of firms in the three high-risk sectors can be improved. In addition to placement & SPP being a low-risk SEO type, it also provides institutional as well as retail investors with the opportunity to participate in the SEO, which promotes fairness between both shareholder groups.

During economic disruptions (Panel B), the Health Care sector appears to have favoured private placements, which is incidentally also classified as the lowest-risk SEO type (as per Table 7.8) from the perspective of abnormal return volatility. Although this SEO type reduces abnormal return volatility, it unfortunately excludes retail shareholders from the capital-raising process, thus introducing problems related to ownership dilution. Since the ASX is a proponent of fairness and inclusion, it may be more appropriate for firms in the Health Care sector to consider the second most ideal SEO type, namely, placement & renounceable rights issue. Firms in the Information Technology sector appear to have used a myriad of SEO types. Although they relied on private placement, they also relied on the two least ideal SEO types, namely, placement & SPP and non-renounceable rights issue. Thus, firms in this sector would benefit by choosing high-ranked (i.e. low-risk) SEO types, that is, private placement or placement & renounceable rights issue. Last, the Industrials sector also did well in their SEO choice by relying primarily on private placements. Yet, many firms in this sector also used the three least ideal SEO types, that is, non-renounceable rights issue, placement & SPP and renounceable rights issue. As in the case of the Information Technology sector, firms in the Industrials sector would benefit by increasing their reliance on private placements or placement & renounceable rights issue.

Table 7.6: Sectoral Risk Scorecard

Panel A: Sector Risk Levels During the Entire Sample Period									
SEO Type	**Number of Independent Variables in Each Category**								
	Low or No Volatility			**Abnormal Return Volatility**					
	(1)	(2)	(1) + (2)	(3)	(4)	(5)	(3) + (4) + (5)	(1) + (2) / Total of (1) to (5)	
	Category 0 (*RRR < 1, less-than-normal return volatility*)	No effect (*RRR of approx. 1*)	Total	Category 1 (*RRR > 1, Low AVAR–GARCH*)	Category 2 (*RRR > 1, Moderate AVAR–GARCH*)	Category 3 (*RRR > 1, High AVAR–GARCH*)	Total	**Probability of experiencing *low* volatility (%)**	**Risk level**
Information Technology	1	2	3	0	0	3	3	50	1
Consumer Discretionary	1	3	4	0	2	2	4	50	2
Consumer Staples	3	0	3	0	0	3	3	50	3
Energy	3	1	4	0	2	3	5	44	4
Materials	1	3	4	2	1	2	5	44	5
Financials	1	1	2	3	4	0	7	22	6
Industrials	1	0	1	2	1	1	4	20	7
Real Estate	1	1	2	1	4	3	8	20	8
Health Care	0	1	1	2	4	0	6	14	9

Note. This table summarises the SEO risk associated with each ASX sector in general (Panel A) as well as during economic disruptions (Panel B). Category 0 (less-than-normal volatility where the RRR < 1) and the no effect category (RRR = 1) are defined as 'low or no volatility'. In contrast, categories 1, 2 and 3 (RRR > 1) are referred to as 'abnormal return volatility'. The second-last column represents the percentage of independent variables that fall into the 'low or no volatility' category (more preferred for firms) relative to the total number of statistically significant variables across all categories. A higher percentage in this column is preferred for it suggests that the given sector has a higher probability of experiencing low volatility and therefore is ranked a lower risk in the list column. In this column, each sector is assigned a ranking from 1 (lowest risk) to 9 (highest risk). The probabilities attached to each sector (second-last column of the table) measure the probability of experiencing *less-than-normal or no volatility*. The percentages range between 0% (i.e. all statistically significant variables instigate abnormal return volatility) to 100% (i.e. all statistically significant variables reduce return volatility). Thus, a sector with a higher percentage has a lower risk and is therefore ranked higher.

Table 7.6: Sectoral Risk Scorecard (Continued)

Panel B: Sector Risk Levels During Economic Disruptions									
SEO Type	Number of Independent Variables in Each Category								
	Low or No Volatility			Abnormal Return Volatility					
	(1)	(2)	(1) + (2)	(3)	(4)	(5)	(3) + (4) + (5)	(1) + (2) / Total of (1) to (5)	
	Category 0 (*RRR < 1, less-than-normal return volatility*)	No effect (*RRR of approx. 1*)	Total	Category 1 (*RRR > 1, Low AVAR–GARCH*)	Category 2 (*RRR > 1, Moderate AVAR–GARCH*)	Category 3 (*RRR > 1, High AVAR–GARCH*)	Total	**Probability of experiencing *low* volatility (%)**	**Risk level**
Energy	2	0	2	0	1	1	2	50	1
Consumer Discretionary	1	2	3	0	0	3	3	50	2
Real Estate	2	1	3	1	0	2	3	50	3
Financials	1	1	2	1	0	2	3	40	4
Materials	2	0	2	0	1	2	3	40	5
Consumer Staples	1	0	1	0	0	2	2	33	6
Health Care	2	0	2	1	2	2	5	29	7
Industrials	1	1	2	2	0	3	5	29	8
Information Technology	1	0	1	1	0	2	3	25	9

Note. This table summarises the SEO risk associated with each ASX sector in general (Panel A) as well as during economic disruptions (Panel B). Category 0 (less-than-normal volatility where the RRR < 1) and the no effect category (RRR = 1) are defined as 'low or no volatility'. In contrast, categories 1, 2 and 3 (RRR > 1) are referred to as 'abnormal return volatility'. The second-last column represents the percentage of independent variables that fall into the 'low or no volatility' category (more preferred for firms) relative to the total number of statistically significant variables across all categories. A higher percentage in this column is preferred for it suggests that the given sector has a higher probability of experiencing low volatility and therefore is ranked a lower risk in the list column. In this column, each sector is assigned a ranking from 1 (lowest risk) to 9 (highest risk). The probabilities attached to each sector (second-last column of the table) measure the probability of experiencing *less-than-normal or no volatility*. The percentages range between 0% (i.e. all statistically significant variables instigate abnormal return volatility) to 100% (i.e. all statistically significant variables reduce return volatility). Thus, a sector with a higher percentage has a lower risk and is therefore ranked higher.

Table 7.7: SEO Types Chosen by Each Sector

Panel A: SEOs Issued during the Entire Sample Period

SEO Type	Health Care	Information Technology	Energy	Consumer Discretionary	Financials	Industrials	Materials	Consumer Staples	Real Estate	Total
Non-renounceable issue	5	1	7	6	0	7	7	0	9	42
Placement	22	15	6	18	29	17	65	2	21	195
Placement & non-renounceable issue	2	3	3	0	3	7	10	3	14	45
Placement & renounceable issue	1	1	0	0	1	1	6	0	1	11
Placement & SPP	10	9	7	11	14	9	18	7	24	109
Renounceable issue	1	2	5	14	10	10	15	3	5	65

Panel B: SEOs Issued During Economic Disruptions

SEO Type	Health Care	Information Technology	Financials	Consumer Discretionary	Energy	Industrials	Materials	Consumer Staples	Real Estate	Total
Non-renounceable issue	0	2	0	2	0	5	5	0	2	16
Placement	13	3	15	6	2	8	27	2	7	81
Placement & non-renounceable issue	0	1	4	6	0	0	12	0	9	32
Placement & renounceable issue	0	0	0	0	0	1	4	0	4	9
Placement & SPP	2	3	8	7	0	2	5	0	6	33
Renounceable issue	1	0	1	3	0	3	4	0	0	12

Note. This table provides a summary of the number of SEOs and the SEO type that were chosen by firms in each sector. The data were obtained from the Morningstar Premium database.

Table 7.8: Chosen SEO Type v. Recommended SEO Type (for the Three Riskiest Sectors)

Panel A: SEOs Issued during the Entire Sample Period				
	Risk Ranking of Recommended SEO Type	Number of Times the SEO Type was Chosen		
		Health Care	Industrials	Real Estate
Placement & SPP	1 (lowest risk)	10	9	24
Non-renounceable issue	2	5	7	9
Private placement	3	22	17	21
Placement & non-renounceable issue	4	2	7	14
Renounceable issue	5	1	10	5
Placement & renounceable issue	6 (highest risk)	1	1	1
Panel B: SEOs Issued During Economic Disruptions				
	Risk Ranking of Recommended SEO Type	Number of times the SEO type was chosen		
		Health Care	Information Technology	Industrials
Private placement	1 (lowest risk)	13	3	8
Placement & renounceable issue	2	0	0	1
Placement & non-renounceable issue	3	0	1	0
Renounceable issue	4	1	0	3
Placement & SPP	5	2	3	2
Non-renounceable issue	6 (highest risk)	0	2	5

Note. This table compares the SEO types used in each sector to the ideal SEO types ranked from 1 (lowest risk – most ideal) to 6 (higher risk – least ideal). The total number of SEOs issued by each sector were sourced from the Morningstar Premium database, and the rankings of each SEO type were obtained from Table 6.8 in Chapter 6.

7.7 Summary

This chapter discussed the determinants of abnormal return volatility during SEO announcements for firms across each ASX sector, during the entire sample period (Model 1) and economic disruptions (Model 2). First, a discussion of the descriptive statistics for each sector was presented for the study period. Following this, a detailed discussion of the Phase 1 and Phase 2 results for each ASX sector was presented. The Phase 1 results showed the changes in abnormal return volatility proxy (*AVAR*) over time for firms in each sector (categorised into high-, moderate- and low-performing sectors). Particular attention was given to the three economic disruption periods because they were characterised by periods of high abnormal return volatility.

Moreover, a comparative analysis of the traditional *AVAR* proxy and the improved *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies was also presented. The improved proxies produced higher abnormal return volatility values for the sectors with a higher degree of volatility clustering, that is, during the dot-com bubble (Consumer Discretionary and Materials) and the GFC (Consumer Discretionary and Energy) periods. All the remaining sectors produced lower abnormal return volatility values with the improved *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies across the three economic disruption periods, compared with the traditional *AVAR* measure, indicating that these sectors exhibited a lower degree of volatility clustering. The analysis of the improved abnormal return volatility proxies confirmed that the traditional *AVAR* proxy had overstated the abnormal return volatility in some sectors but understated it in others. Hence, the improved proxies were used as the dependant variable for the regression in Phase 2.

In Phase 2, the MLR results were presented, highlighting the determinants of abnormal return volatility for each sector across the entire sample period (Model 1) and economic disruptions

(Model 2). Although the findings suggest that each sector experienced varying levels of abnormal return volatility in response to changes in each independent variable, some overall trends were identified. Across the entire sample period, *AVOL*, *CIT* and *AMV* had the most widespread impact on abnormal return volatility across most sectors. In contrast, during economic disruptions, no specific variables had a consistent impact on abnormal return volatility. Robustness tests were also performed, and the results confirmed that the regression results were largely unchanged. This chapter concluded with a discussion of the implications of the results, which involved the comparison of the SEO decisions made by firms in high-risk sectors relative to the ideal SEO types (outlined in Table 6.8 in Chapter 6). During the entire sample period, the highest-risk sectors were Industrials, Real Estate and Health Care. Firms in these sectors favoured private placements, when, in fact, the placement & SPP was a low-risk SEO and therefore a more ideal choice. During economic disruptions, the highest-risk sectors were Health Care, Information Technology and Industrials, and in these periods, private placements were considered the most ideal, whereas non-renounceable rights issues were least ideal. It was observed that private placements were favoured by each of the three sectors, signalling that firms are choosing the appropriate SEO type from the perspective of reducing abnormal return volatility. However, in addition to private placements, the Information Technology and the Industrials sectors relied on two of the lowest-ranked (highest-risk) SEO types, placement & SPP and standalone non-renounceable rights issue. To help reduce their contribution to abnormal return volatility, it would be beneficial for firms in these two sectors to consider the use of private placements or placement & renounceable rights issue (if they wish to promote fairness between institutional and retail shareholders who participate in the SEO).

In the next chapter, the final conclusions of the thesis are presented based on the results discussed in Chapters 5 to 7. In the conclusion chapter, a summary of the results will be provided along with its implications for firms that issue SEOs, their investors and capital market regulators, followed by recommendations for further research.

Chapter 8: Conclusion and Recommendations

8.1 Introduction

Since firms in Australia are prolific issuers of SEOs, investors can expect ASX-listed firms to continue relying on SEOs to fund their operations and replenish their balance sheets during economic disruptions. Firms prefer an SEO owing to its numerous benefits, especially during economic disruptions, including quick turnaround times, the freedom to choose the amount of capital to be raised and unlimited capital-raising rounds. When firms announce that they intend to conduct an SEO, the financial markets digest this information, resulting in an increase in stock return volatility. For this reason, it is reasonable to assume that each time an SEO announcement is released, return volatility will follow and will be an ongoing aspect of the SEO issuance process. When a firm undertakes an SEO, it has a choice between a range of SEO types to use. Nevertheless, each SEO type should not be treated equally because some SEO types instigate larger investor reactions than others. This means that normal or expected levels of stock return volatility may translate into *abnormal* levels of stock return volatility, which can become a concern for firms. An abnormal level of stock return volatility is a concern because it can result in larger negative effects on investors' portfolios and is likely to deter them from participating in future equity-raising rounds, which can hinder a firm's equity-raising prospects. Therefore, the purpose of this thesis is to reveal that abnormal return volatility does exist across various SEO types and across each ASX sector. Further, this thesis conducted an in-depth investigation to understand the determinants that have the largest effect on abnormal return volatility. The resulting insights will not only help firms to reduce the negative volatility impact of their SEO choices on their shareholders but will also help them to improve the stability of their share price. This will boost shareholder confidence and ultimately support the firms' ability to raise additional capital easily using SEOs in the future.

This research employed empirical data on ASX 200 listed firms for 1998–2020 from Refinitiv Eikon and Morningstar DatAnalysis to address the following research objectives:

1. Analyse the extent to which abnormal return volatility occurs in standalone, restricted and combined SEO types.
2. Identify the extent to which abnormal return volatility transpires in each Australian sector by highlighting similarities and differences in high-, moderate- and low-performing sectors.
3. Examine the degree to which abnormal return volatility changed during economic disruptions compared with the entire sample period.
4. Ascertain and evaluate the hypothesised determinants of the abnormal return volatility for each SEO type and sector in order to provide tailored SEO recommendations to firms.

The overarching intent of this thesis is to provide firms, shareholders and policymakers with a comprehensive understanding of the factors that induce abnormal return volatility during SEO announcements. In addition to using the traditional *AVAR* measure, this thesis developed alternative proxy measures for abnormal return volatility, namely, *AVAR–GARCH* and *AVAR–GJR–GARCH*. These proxies improved the accuracy of the traditional measure by incorporating the stylised features commonly observed in the volatility of stock returns (i.e. heteroscedasticity and a leptokurtic distribution), which is not captured by the traditional *AVAR* measure. Moreover, the *AVAR–GJR–GARCH* proxy provides additional improvements by incorporating the leverage effect within the measurement of abnormal return volatility.

The two improved proxies were then used to undertake multinomial logistic regression analysis of panel data. Two general models were developed to ascertain how abnormal return volatility manifested during various points in time. The first model, Model 1, required the use of data that span the entire sample period, whereas Model 2 only considered data for economic disruption periods (i.e. the dot-com bubble, the GFC and the COVID-19 pandemic). Moreover, to provide specificity and a wide breath of coverage, these regressions were employed for each SEO type as well as each ASX sector. The results provide compelling evidence, which confirms that varying degrees of abnormal return volatility are indeed observed for each SEO type and sector. Following this analysis, three robustness tests were also conducted to ensure the reliability of the results. The statistical significance of the coefficients in the regression results for each robustness test remained unchanged relative to the base models, confirming that the results are reliable.

8.2 Research Findings and Implications

The results of thesis showed that abnormal return volatility is indeed present, with variations occurring in each SEO type and sector. The results are subdivided across three chapters: Chapter 5 provided the preliminary testing results and the Australian aggregate market regression results. Chapter 6 provided the regression results for each SEO type and Chapter 7 provided the regression results for each ASX sector. Further, each chapter presented Phase 1 and Phase 2 results. Phase 1 was carried out to answer research objectives (i), (ii) and (iii), which involved highlighting the existence of abnormal return volatility as well as comparing the improved *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies to the traditional *AVAR* measure. This comparison was made to confirm that the traditional *AVAR* proxy inaccurately captured the size of abnormal return volatility because it fails to account for volatility clustering, a commonly observed phenomenon of stock returns. Phase 2 was conducted to answer objective (iv), which involved the examination of the determinants of abnormal return volatility identified for each SEO type and sector in Phase 1.

Chapter 5 presented the first set of results of this thesis, which examined the determinants of abnormal return volatility across the Australian aggregate market. The preliminary tests results confirmed that the variables did not suffer from multicollinearity and were stationary. In Phase 1, the findings support the predictions set out under Hypothesis 1, namely, that SEO announcements do indeed elicit abnormal return volatility and that the volatility is exacerbated during economic disruptions. Moreover, on comparing the traditional abnormal return volatility measure (*AVAR*) with the improved proxies (*AVAR–GARCH* and *AVAR–GJR–GARCH*), the results show that in many circumstances, the *AVAR* measure overstated the true degree of abnormal return volatility. In Phase 2, two models were estimated: Model 1 and Model 2. The results of Model 1 (entire sample period) highlighted that *AVOL*, *DISC*, *CIT*, MB, *DIS* and *AMV* all contributed to an increase in abnormal return volatility, whereas *BAS* and *SIZE* reduced a firm's return volatility. With respect to Model 2 (economic disruptions), the findings show that *DISC* and *SIZE* were the main contributors to abnormal return volatility, whereas *AVOL* and *MBV* reduced the return volatility.

Chapter 6 discussed the determinants of abnormal return volatility for each SEO type, during the entire sample period (Model 1) and economic disruptions (Model 2). The results highlighted that firms favoured standalone SEOs (particularly private placements) up until 2012 but have since shifted towards using combined SEOs. In this chapter, comparisons were drawn between the factors that drive abnormal return volatility for the standalone SEO and those that drive it for combined SEOs. The Phase 1 results in this chapter showed that abnormal return volatility (based on the traditional abnormal return volatility measure: *AVAR*) varied across each SEO type, with the highest levels being felt by firms during economic disruptions.

During the dot-com bubble and the GFC, standalone SEOs experienced higher levels of abnormal return volatility, and standalone renounceable rights issues were the most affected, lending support to Hypothesis 2(a). However, during the COVID-19 pandemic, the abnormal return volatility shifted more towards combined SEOs, with placement & non-renounceable rights issue being most affected. With respect to the improved abnormal return volatility proxies (*AVAR–GARCH* and *AVAR–GJR–GARCH*), the results are consistent with those described in Chapter 5, where the improved proxies produced higher abnormal return volatility values for the SEO types that had a higher degree of volatility clustering, and a lower abnormal return volatility for SEO types that had a lower degree of volatility clustering. It should be noted that in Phase 2, Hypotheses 3(a) to 12(a) and 12(b) were individually assessed (resulting in the acceptance or rejection of each hypothesis under Models 1 and 2 within Chapter 6) because each independent variable had a distinct effect on abnormal return volatility for each SEO type. Despite each SEO type experiencing varying degrees of abnormal return volatility in response to each determinant, nonetheless, some overall trends were identified.

Across the entire sample period, *AVOL*, *MBV*, *DIS* and *AMV* had the most widespread impact on abnormal return volatility across most SEO types, whereas *SIZE* was the largest contributor to the reduction in return volatility. In contrast, during economic disruptions, *MS*, *COE* and *SIZE* were responsible for eliciting abnormal return volatility across most SEO types, whereas *AVOL* and *CIT* were the largest contributors to a reduction in return volatility. This chapter also discussed the implications of the results, which detailed the most ideal (lowest risk) and least ideal (highest-risk) SEO types for firms to choose. During the entire sample period, the most ideal (lowest risk) SEO type was placement & SPP and the least ideal (highest risk) was placement & renounceable rights issue. During economic disruptions, private placements were considered the most ideal (lowest risk) SEO type, whereas the non-renounceable rights issue was the least ideal (highest risk) option. With respect to the remaining SEO types, their risk rating resided between the high- and low-risk SEO types, which are presented in Table 6.8 in Chapter 6.

Chapter 7 analysed the impact of a set of 11 determinants on abnormal return volatility during SEOs for firms in each ASX sector, across the entire sample period (Model 1) and economic disruptions (Model 2). Phase 1 presented mixed results. First, abnormal return volatility was evident in all high- and moderate-performing sectors and it intensified during economic disruptions, lending support to Hypothesis 2(b). The only exceptions were the Consumer Staples sector during the dot-com bubble and the Industrials sector during the COVID-19 crisis. On average, the Energy and the Health Care sectors were the most sensitive to SEOs, evidenced by higher abnormal return volatility. Moreover, the Real Estate sector (classified as a low-performing sector) also experienced abnormal return volatility during two of the three economic disruptions (the GFC and the COVID-19 pandemic). Again, similarly to the results in Chapters 5 and 6, a comparison between the traditional *AVAR* proxy and the improved *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies confirmed the improved proxies produced higher abnormal return volatility values for the sectors with a higher degree of volatility clustering, and a lower abnormal return volatility for sectors with a lower degree of volatility clustering.

In Phase 2 of Chapter 7, Hypothesis 3(b) to 11(b) 12(c) were also individually assessed for Models 1 and 2. The results also revealed some overall trends across the various ASX sectors. During the entire sample period, *AVOL*, *CIT* and *AMV* had the most widespread impact on abnormal return volatility across most sectors. In contrast, during economic disruptions, no specific variables consistently affected abnormal return volatility across all sectors. A discussion of the implications of the results revealed that the highest-risk sectors were Industrials, Real Estate and Health Care during the entire sample period. Further, firms across these sectors favoured private placements, despite placement & SPP being classified as lower risk. During economic disruptions, Health Care, Information Technology and Industrials were considered the highest-risk sectors. Among these three sectors, private placements appeared to be most popular, signalling that firms were choosing the appropriate SEO type since private placements were considered the most ideal during economic disruptions. However, the Information Technology and the Industrials sectors also relied heavily on two of the highest-risk SEO types, that is, placement & SPP and standalone non-renounceable rights issue, thereby increasing their risk rating. Firms may have also relied on the two SEO types (in addition to private placements) because private placements do not include a retail shareholder participation component, whereas these two types do have this provision. Although firms may have chosen these SEO types for the right reasons (to support equal opportunity for both institutional and retail shareholders), they did not serve firms in the Information Technology and the Industrials sectors well. Instead, to help reduce their contribution to abnormal return volatility, it would be beneficial for firms in these sectors to consider the use of placement & renounceable rights issue if they wish both institutional and retail shareholders to participate in the SEO, because both these types were associated with lower levels of abnormal return volatility.

The fact that the abnormal return volatility varies for each SEO and across sectors highlight that firms should remain flexible in choosing the SEO type rather than preferring a single type. Summarising from Chapter 1 onward, this discussion provides answers to each of the five overreaching research questions. Next, the answers to the research questions are summarised:

RQ1: Is there a significant increase in abnormal return volatility across the aggregate market during periods of economic disruption compared with the entire sample period and what are its determinants?

Yes, as highlighted in Chapter 5, abnormal return volatility increased substantially during economic disruption periods. This finding implies that periods of economic uncertainty can lead to a higher degree of uncertainty when firms issue SEO announcements during these times, which translates into higher levels of abnormal return volatility. Moreover, firms experienced a higher degree of abnormal return volatility in response to the COVID-19 pandemic than they did during the GFC and the dot-com bubble periods. This finding indicates that shareholders are more sensitive to SEOs issued during a health-related crisis than to those issued during an economic crisis.

Across the entire sample period, *AVOL*, *DISC*, *CIT*, *MBV*, *DIS* and *AMV* were all determinants of abnormal return volatility for the aggregate market. In contrast, an increase in *BAS* and *SIZE* reduced the risk of firms experiencing abnormal return volatility. During economic disruptions, *DISC* and *SIZE* continued to instigate abnormal return volatility, whereas increases in *AVOL* and *MBV* resulted in firms experiencing less-than-normal volatility. Moreover, whilst *AMV* instigated moderate levels of abnormal return volatility across the whole period, it did not have an impact during economic disruptions. Last, *ILLIQ* produced RRR coefficients close to 1 for both the entire sample period and periods of economic disruptions, indicating that it had no effect on abnormal return volatility during SEOs. These results confirm that each of the determinants have varied effects on a firm's abnormal return volatility across the aggregate market. This led to a closer examination of the determinants for each SEO type, which was addressed in research question 2 and 3.

RQ2: Which SEO types exhibit higher and lower levels of abnormal return volatility during SEO announcements?

Unlike the traditional *AVAR* proxy, the improved *AVAR–GARCH* and *AVAR–GJR–GARCH* proxies provided more accurate measurements of abnormal return volatility by incorporating volatility clustering within the proxy. According to these improved proxies, placement & renounceable rights issue, standalone renounceable rights issue and placement & non-renounceable rights issue were associated with higher levels of abnormal return volatility during the entire sample period. This finding implies that abnormal return volatility is prominent across both standalone and combined SEOs. In contrast, three types, placement & SPP, standalone non-renounceable rights issue and standalone private placement, were associated with lower levels of volatility. A detailed summary of these SEO types is provided in Table 6.8 in Chapter 6.

RQ3: What are the determinants of the abnormal return volatility for each SEO type?

Although various determinants affected each SEO type, some general trends were found. Across the entire sample period, *AVOL*, *MBV*, *DIS* and *AMV* had the most widespread impact on abnormal return volatility across all SEO types, whereas *SIZE* was the largest contributor to the reduction in volatility. In contrast, during economic disruptions, *MSA*, *COE* and *SIZE* instigated abnormal return volatility across most SEO types, whereas *AVOL* and *CIT* were the largest contributors to a reduction in volatility. The impact of each determinant on abnormal return volatility for each SEO type is discussed in detail in Tables 6.6 and 6.7 in Chapter 6.

Each SEO type was also assigned a risk rating based on the number of statistically significant determinants that instigated abnormal return volatility. According to these risk rankings, across the entire sample period, the lowest-risk SEO type, and therefore the most ideal, was placement & SPP, whereas the highest-risk SEO type, and thus the least ideal, was placement & renounceable rights issue. During economic disruptions, these risk rankings changed, with private placement being considered the lowest-risk SEO type and standalone non-renounceable rights issue being classified as the riskiest.

RQ4: Which Australian sectors exhibit abnormal return volatility in response to SEO announcements and is this exacerbated during economic disruptions?

Abnormal return volatility was found to affect firms across all sectors during the entire sample period, which indicates that all sectors react to SEO announcements. As expected, during economic disruptions, the abnormal return volatility was indeed exacerbated, and firms in high- and moderate-performing sectors experienced higher levels of abnormal return volatility, compared with firms in low-performing sectors. Moreover, on examining each economic disruption, it was found that the COVID-19 pandemic had a higher effect on the abnormal return volatility across most sectors than did the GFC and the dot-com bubble periods. The full results are reported in Tables 7.2 and 7.3 in Chapter 7, and a detailed discussion of these results is provided in Section 7.3.

RQ5: What are the determinants of the abnormal return volatility found across each Australian sector?

Although various determinants affected each sector individually, some overall trends were identified. Across the entire sample period, *AVOL*, *CIT* and *AMV* had the most widespread impact on abnormal return volatility across most sectors. In contrast, during economic disruptions, no specific variables consistently affected abnormal return volatility across all sectors. It should be noted that the results vary across sectors. Thus, the impact of the determinants on abnormal return volatility across each sector is discussed in detail in Section 7.4 in Chapter 7 and the detailed results are tabulated in Tables 7.4 and 7.5.

8.3 Research Recommendations

8.3.1 Retail Shareholders

The results of this research will be of interest to retail investors (e.g. individual retail investors, hedge funds, individuals with self-managed superannuation funds and high-net-worth individuals). The results will benefit these groups by allowing shareholders to understand the abnormal return volatility dynamics around SEO announcements, which they can factor into their risk management criteria. With respect to investment firms specifically, since it is not uncommon for institutions to invest according to sectoral performance, the results of this research will help identify the sectors that are considered higher risk and only attribute those to aggressive investment strategies. Investors can also use these findings to understand the SEO risk profile of each firm based on the SEO type they use and decide whether they should invest in it.

If an investor or an investment firm seeks to participate in a low-risk SEO during the entire sample period, they should search for a firm that primarily utilises placement & SPP or standalone non-renounceable right issues. Moreover, if they seek to find a sector in order to actively participate in SEOs with higher performance and lower risk, the Energy, the Information Technology or the Consumer Staples sectors would be ideal. This is because these SEOs have the ideal combination of residing in high- and moderate-performing sectors that also experience lower levels of abnormal return volatility. The sectors to avoid would be the Health Care and the Real Estate sectors for both are associated with higher abnormal return volatility and are thus high-risk investments. In addition, if an investor plans to participate in SEOs during economic disruptions, it would be beneficial to purchase the shares of firms that use private placements or placement & renounceable rights issue, since both types are associated with lower overall abnormal return volatility.

8.3.2 Portfolio Managers

The results of this research would benefit portfolio managers of actively managed funds and superannuation funds because it provides them with empirical evidence to support their risk management strategy during the asset allocation process. To help reduce the risk exposure of the portfolios that they construct and manage, it would be beneficial to choose firms with a lower risk of experiencing abnormal volatility. In this case, the selection of firms that primarily rely on placement & SPP or non-renounceable rights issue as their preferred SEO type would help to minimise the risk of investors experiencing abnormal return volatility. This metric will allow portfolio managers to capitalise on an additional risk metric to help them manage their risk exposure to a portfolio of stocks that use different SEO types. Moreover, portfolio managers can also use portfolio rebalancing to redistribute the stocks in their portfolios during economic disruptions to those that use SEO types with a lower risk. During economic disruptions, they can substitute the firms that use placement & SPP and non-renounceable rights issue with firms that primarily use private placement and placement & renounceable rights issue because these SEO types experience the lowest levels of abnormal return volatility during those periods.

Portfolio managers can also capitalise on the risk levels identified for each sector in response to SEO announcements. They can help to reduce the overall portfolio volatility by choosing to invest into sectors that experience the lowest levels of abnormal return volatility. During an entire sample period, Information Technology, Consumer Discretionary and Consumer Staples would be the ideal choices for they are the least risky during SEO announcements. In contrast, the Health Care, the Real Estate and the Industrials sectors should be avoided. With respect to economic disruptions, portfolio managers could also undertake portfolio rebalancing during this time and redistribute the portfolio to include stocks from firms in the Energy, the Consumer

Discretionary and the Real Estate sectors and avoid the Health Care, the Industrials and the Information Technology sectors.

8.3.3 Regulators and Market Markers

This research has presented a risk framework to help firms identify the ideal SEO type to minimise abnormal return volatility during SEO announcements. Understandably, firms favoured the SEO types that consisted of a placement component because of their benefits (i.e. large block purchases and quick turnaround time). However, these benefits are obtained at the cost of the holdings of the existing investors becoming diluted and their experiencing abnormal return volatility during SEOs. Thus, it clear that firms require further guidance during the SEO decision-making process. The ASX (a market maker) and ASIC (financial market regulator) ultimately expect firms to choose an SEO type that proves to serve not only the interests of the firm but also their shareholders (ASX 2010). Thus, the primary aim of this thesis is to help firms strike the right balance between raising sufficient capital while minimising the abnormal return volatility impact on their shareholders. This can be achieved by helping firms understand that they should not treat all SEO types as equal during the capital-raising process. Given that the returns of a long-term investor are based upon the success of a firm, this study acknowledges that during the entire sample period, it would be unrealistic to employ a 'one-size-fits-all' approach and mandating all firms to use the same SEO type. Instead, it is appropriate for the ASX to require firms (integrated within their continuous disclosure requirements) to provide a *statement of intent* or a *disclosure statement* to investors detailing which SEO type the firm has chosen as well as providing a detailed rationale for their choice. This requirement will help to improve information transparency and improve investor confidence, thereby allowing shareholders to make more informed investment decisions. This is important particularly during economic disruptions when the abnormal return volatility is intensified. Such a requirement may ultimately enable publicly listed firms to improve the ease at which it can raise capital multiple times in the future.

Another policy implication is that during economic disruptions, capital market regulators (e.g. ASIC) could temporarily mandate firms to choose a combined SEO (e.g. placement & SPP) as a first preference to raise equity. Although the use of combined SEOs is already advocated by the ASX, it is still upon the discretion of each firm to choose the appropriate SEO type. In this regard, private placements are more ideal, but unfortunately exclude retail shareholders in the capital-raising process during a volatile time, causing greater pain to these shareholders. Thus, using a combined SEO would give institutional and retail shareholders an equal opportunity to participate in the SEO.

8.4 Limitations and Future Research

Although this thesis does present compelling evidence about the presence of abnormal return volatility and its determinants, nonetheless, it has some limitations. The first is that it does not separate volatility into positive and negative components. This means that the abnormal return volatility measure does not differentiate between a sudden spike upwards (showing optimism and positivity towards the SEO) or downwards (showing negativity) in the stock price after the SEO announcements. Since volatility only has a positive sign, it is difficult to ascertain whether the reaction to the SEO announcement was positive or negative. This could be researched further because some SEO types and sectors may perceive SEO announcements differently, depending on whether shareholders are bullish or not about the firm/sector. Another limitation of this study is that it focused on the Australian market. Although Australian firms are prolific issuers of SEOs, firms in many other larger developed economies (e.g. the US and the United Kingdom) also utilise SEOs and these markets can potentially experience higher levels of abnormal return volatility. Thus, an area of future research could be to comparatively explore the abnormal return volatility effects in these economies.

Another limitation of this research is that is does not consider the effects of the share buyback scheme that firms commonly undertake. In this scheme, the firm repurchases its shares from shareholders and reabsorbs these to reduce the number of shares circulating in the market. This provides the benefit of increasing the ownership percentage of existing shareholders, which provides more capital for the firm for future capital-raising needs. Theoretically, this is a positive signal to shareholders because the process of buying back shares requires the firm to have generated positive cash flow to undergo this process – a sign of financial strength. The fact that it also reduces the number of shares outstanding provides existing shareholders with a slightly larger ownership percentage in the business. This should theoretically reduce the abnormal return volatility of the firm. Including this type of event may be a useful area of future research to ascertain whether a firm is able to reduce the impact of abnormal return volatility from share buyback schemes after instigating abnormal return volatility from the SEO prior to it.

The final limitation of this research is that it focuses only on equity issuances. However, debt securities (e.g. short-term unsecured notes and high-yield long-term bonds) are also very commonly issued by ASX-listed firms, which may also instigate abnormal return volatility. This could be an area of further research and could help reinforce or challenge existing capital structure theories to help identify the right balance of debt and equity in a business.

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Appendices

Appendix 1: SEOs and Sectors Tested

Appendix 1.1: SEO Types Estimated in Phase 2

SEO Type	Model 1 (Entire Sample Period)	Model 2 (Economic Disruption Periods)
Non-renounceable rights issue	Yes	Yes
Placement	Yes	Yes
Placement & non-renounceable rights issue	Yes	Yes
Placement & SPP	Yes	Yes
Renounceable rights issue	Yes	Yes
Placement & renounceable rights issue	Yes	Yes
Bonus issue	No – insufficient observations	No – insufficient observations
Share purchase plan (SPP)	No – insufficient observations	No – insufficient observations
Renounceable & non-renounceable issue	No – insufficient observations	No – insufficient observations

Note. Although bonus issues, SPPs and renounceable & non-renounceable rights issues were not included in Phase 2, they were still considered in Phase 1 as econometric modelling was undertaken in this instance. Therefore, there was no requirement to have a minimum sample size to measure the changes in *AVAR*, *AVAR–GARCH* and *AVAR–GJR–GARCH* over the study period.

Appendix 1.2: Sectors Estimated in Phase 2

Sector	Model 1 (Entire Sample Period)	Model 2 (Economic Disruption Periods)
Consumer Discretionary	Yes	Yes
Financials	Yes	Yes
Health Care	Yes	Yes
Industrials	Yes	Yes
Information Technology	Yes	Yes
Materials	Yes	Yes
Real Estate	Yes	Yes
Consumer Staples	Yes	Yes
Energy	Yes	Yes
Utilities	No – insufficient observations	No – insufficient observations
Communication Services	No – insufficient observations	No – insufficient observations

Appendix 2: Robustness Tests for each SEO Type

Appendix 2.1: Robustness Test 1 – Robust Standard Errors

Model 1: Entire Sample Period

	Standalone SEOs						Restricted SEOs			Combined SEOs								
	Renounceable Rights Issue			Non-renounceable Rights Issue			Placement			Placement & Non-renounceable Rights Issue			Placement & SPP			Placement & Renounceable Rights Issue		
	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Variable	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR
AVOL	1.24***	1.48***	1.62**	1.35***	1.42***	1.45***	1.15***	1.18***	1.20***	1.15***	1.29***	1.53***	1.48***	1.61***	1.76***	1 12*	1.26***	1.24**
	(0.10)	(0.22)	(0.32)	(0.08)	(0.10)	(0.11)	(0.06)	(0.07)	(0.07)	(0.05)	(0.07)	(0.12)	(0.08)	(0.11)	(0.14)	(0.07)	(0.11)	(0.11)
DISC	1.11*	0 94	0.83	1.00	1.10	0.96	1.04	1.04	0.77**	1.03	1.08*	1.25***	1.18***	1 23***	1.43***	0.88	0.01	0.07
	(0.07)	(0.13)	(0.10)	(0.08)	(0.12)	(0.17)	(0.06)	(0.10)	(0.10)	(0.03)	(0.05)	(0.09)	(0.06)	(0.09)	(0.16)	(0.24)	(0.02)	(0.32)
ILLIQ	1.04***	1.04***	1.04**	1.02***	1.02***	1.02***	1.01***	1.01***	1.02***	1.01***	1.02***	1.02***	1.01***	1.01***	1.02***	1.01***	1.02***	1.01***
	(0.01)	(0.01)	(0.02)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
BAS	0.78***	0.81	1.04	0.93	1.05	0.84	1.06	1.08	1.02	0.91	1.03	0.89	1.03	1.06	0.93	0.80	0.82	0.96
	(0.05)	(0.11)	(0.12)	(0.07)	(0.11)	(0.13)	(0.03)	(0.06)	(0.11)	(0.06)	(0.09)	(0.17)	(0.04)	(0.08)	(0.14)	(0.12)	(0.27)	(0.31)
MSA	0.99	1.01	0.99	1.00	0.99	0.98	1.01*	1.02**	1.04***	1.00	1.03	0.86***	1.03***	1.04***	1.03	1.01	1.14	0.91
	(0.01)	(0.02)	(0.05)	(0.01)	(0.02)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.04)	(0.01)	(0.01)	(0.03)	(0.02)	(0.11)	(0.22)
CIT	1.02	1 13	0.74	0.99	0.78	0.00***	3.00***	2.09*	1.26	1.07	1.03	0.51	0.86	1.76	0.64	0.47	0.00***	0.00***
	(0.51)	(1.01)	(0.75)	(0.57)	(0.87)	(0.00)	(0.62)	(0.89)	(0.73)	(0.41)	(0.73)	(0.66)	(0.29)	(0.75)	(0.83)	(0.72)	(0.00)	(0.00)
COE	1.04***	1.01	1.02	0.97***	0.96***	0.98	0.99**	0.98***	1.01	1.02*	1.03**	1.10***	0.99	0 97*	0.97	1.04**	1.07**	1.09***
	(0.01)	(0.03)	(0.03)	(0.01)	(0.02)	(0.02)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.03)
MBV	1.58***	1.66***	1.95**	1.14	1.27**	1.42*	1.10**	1.18**	1.22*	0.87*	1.19	1.74**	1.03	1.02	0.86	2.01**	1.99	3.58*
	(0.19)	(0.30)	(0.57)	(0.10)	(0.15)	(0.29)	(0.04)	(0.09)	(0.15)	(0.07)	(0.14)	(0.39)	(0.07)	(0.13)	(0.20)	(0.56)	(1.39)	(2.57)
SIZE	0.89*	0.78	0.75	1.01	0.99	1.07	0.96*	0.87***	0.92	1.27***	1.19**	1.30**	0.90***	0.78***	0.82	1.03	0.96	0.70
	(0.06)	(0.12)	(0.17)	(0.07)	(0.10)	(0.16)	(0.02)	(0.03)	(0.07)	(0.06)	(0.10)	(0.14)	(0.04)	(0.06)	(0.11)	(0.11)	(0.33)	(0.29)
DIS	3.63***	0.86	1.31	3.92***	1.16	0.00***	1.88***	1.97***	3.41***	1.65*	1.96	2.77	1.70***	1.60*	1.10	2.62*	3.59	10.40
	(0.96)	(0.61)	(1.30)	(1.21)	(0.75)	(0.00)	(0.23)	(0.40)	(1.18)	(0.49)	(0.83)	(1.84)	(0.26)	(0.45)	(0.69)	(1.43)	(5.41)	(19.52)
AMV	1.04	1 58**	0.97	1.37**	1.08	0.41*	1.09*	1.41***	1.24*	1.04	1.10	0.96	1.10*	1 16*	1.22	1 94***	1.49	1.35
	(0.13)	(0.30)	(0.31)	(0.17)	(0.29)	(0.19)	(0.05)	(0.10)	(0.16)	(0.11)	(0.14)	(0.26)	(0.06)	(0.10)	(0.23)	(0.39)	(0.63)	(0.64)
Constant	0.09	0.49	1.05	0.05*	0.06	0.00**	0.25**	0.49	0.01***	0.00***	0.00***	0.00***	0.50	3.64	0.20	0.00**	0.00	0.41
	(0.15)	(1.95)	(5.49)	(0.09)	(0.14)	(0.01)	(0.14)	(0.45)	(0.02)	(0.00)	(0.00)	(0.00)	(0.50)	(6.40)	(0.64)	(0.00)	(0.00)	(3.66)

Note. This table provides the regression results for each SEO type during the entire sample period (Model 1). It displays the relative risk ratios (RRR) and standard errors in parentheses of each variable in each *AVAR–GARCH* category. An RRR coefficient of less than 1 indicates that a firm was more likely to experience less-than-normal volatility, an RRR coefficient of 1 (or close to 1) shows that the independent variable had no effect on a firm's abnormal return volatility and an RRR coefficient greater than 1 denotes that a firm was more likely to experience abnormal return volatility. The abnormal return volatility (*AVAR–GARCH*) is classified into three categories: category 1 (low abnormal return volatility), category 2 (moderate abnormal return volatility) and category 3 (high abnormal return volatility). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Appendix 2.1: Robustness Test 1 – Robust Standard Errors (Continued)

Model 2: Economic Disruptions

	Standalone SEOs						**Restricted SEOs**			**Combined SEOs**								
	Renounceable Rights Issue			**Non-renounceable Rights Issue**			**Placement**			**Placement & Non-renounceable Rights Issue**			**Placement & SPP**			**Placement & Renounceable Rights Issue**		
	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Variable	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR
*AVOL*DIS*	0.65**	0.96	0.73	0.82	1.13	0.88	0.87**	0.85**	0.90	1.51*	1.35	2.09**	0.79**	0.75**	0.71**	20.97**	12.31*	23.43**
	(0.12)	(0.20)	(0.19)	(0.14)	(0.29)	(0.19)	(0.06)	(0.06)	(0.08)	(0.36)	(0.37)	(0.69)	(0.09)	(0.11)	(0.11)	(27.63)	(15.77)	(31.70)
*DISC*DIS*	0.00**	0.00**	0.00	0.01	0.16	18.58	3.41	6.85	0.60	1.14	1.35	0.99	4.61	3.30***	597.18	0.04	0.00***	0.00*
	(0.00)	(0.00)	(0.00)	(0.02)	(1.52)	(68.88)	(2.56)	(9.10)	(1.26)	(0.14)	(0.29)	(0.25)	(7.45)	(6.99)	(308.28)	(0.18)	(0.00)	(0.00)
*ILLIQ*DIS*	1.02	0.98	1.04	1.01	1.02**	0.98***	1.00	1.00	1.01	1.04***	1.07***	0.98	4.06***	9.01***	5.51***	1.62	61.50	15.92**
	(0.04)	(0.05)	(0.05)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)	(0.03)	(1.58)	(4.22)	(3.17)	(9.43)	(5.01)	(1.14)
*BAS*DIS*	1.30	0.96	0.66	0.94	0.72	1.50**	1.05	1.07	0.89	1.08	0.79	0.98	1.07	0.97	1.99**	0.27	0.00***	0.95
	(0.21)	(0.45)	(0.34)	(0.16)	(0.34)	(0.31)	(0.08)	(0.13)	(0.17)	(0.20)	(0.22)	(0.31)	(0.10)	(0.17)	(0.58)	(0.34)	(0.01)	(0.40)
*MSA*DIS*	1.08***	0.86	0.92	1.03	0.69**	1.15*	1.02	1.02	0.99	1.01	1.18**	0.89	0.98	0.96	0.87	1.00	1.00	1.00
	(0.03)	(0.10)	(0.08)	(0.06)	(0.12)	(0.09)	(0.02)	(0.03)	(0.05)	(0.05)	(0.09)	(0.09)	(0.03)	(0.04)	(0.11)	(0.00)	(0.00)	(0.00)
*CIT*DIS*	0.00***	0.00***	0.00***	0.36	0.00***	2.15***	1.22	0.30	0.00***	0.54	0.00***	18.57	0.90	1.32	0.00***	0.00***	0.14	0.05
	(0.00)	(0.00)	(0.00)	(0.45)	(0.00)	(2.14)	(0.57)	(0.35)	(0.00)	(0.67)	(0.00)	(45.24)	(0.67)	(1.15)	(0.00)	(0.00)	(0.25)	(0.10)
*COE*DIS*	1.50*	1.50*	3.05*	1.00	1.00	1.02	1.01	1.03	0.92**	1.07	1.01	1.49**	1.01	1.02	0.97	1.46	1.62***	1.79***
	(0.36)	(0.35)	(1.89)	(0.02)	(0.03)	(0.03)	(0.01)	(0.02)	(0.03)	(0.05)	(0.05)	(0.26)	(0.02)	(0.03)	(0.05)	(0.85)	(5.06)	(8.69)
*MBV*DIS*	2.48**	0.80	0.61	0.70	0.54	5.32***	0.90	0.48***	0.64	0.74	1.85	0.08**	1.00	1.09	2.09**	0.03	0.00***	0.00***
	(0.96)	(0.27)	(0.37)	(0.27)	(0.47)	(2.38)	(0.11)	(0.11)	(0.19)	(0.33)	(0.90)	(0.09)	(0.15)	(0.27)	(0.74)	(0.19)	(0.00)	(0.00)
*SIZE*DIS*	1.92*	1.41	1.08	0.87	0.74	1.85***	1.12**	1.08	0.89	0.86	0.72	0.87	1.30**	1.24	1.06	1.70	0.00***	0.01
	(0.65)	(0.59)	(0.91)	(0.11)	(0.20)	(0.28)	(0.05)	(0.08)	(0.11)	(0.12)	(0.19)	(0.21)	(0.14)	(0.24)	(0.49)	(10.95)	(0.00)	(0.05)
*AMV*DIS*	0.78	0.66	0.43	1.19	1.97	4.53***	0.93	0.98	0.49**	0.80	0.53**	0.56	1.26*	0.94	1.58	0.41**	0.00**	0.21***
	(0.20)	(0.21)	(0.40)	(0.29)	(1.23)	(2.40)	(0.09)	(0.14)	(0.17)	(0.18)	(0.16)	(0.25)	(0.17)	(0.19)	(0.53)	(0.16)	(0.00)	(0.12)

Note. This table presents the regression results for each SEO type during economic disruptions (Model 2), which shows the interactions (in bold) of economic disruptions (*DIS*) with each independent variable as a separate regression, holding all other independent variables constant (a total of 10 independent regressions). The models were executed in this way to prevent the potential for multicollinearity of the *DIS* variable with other instances of *DIS* within the same regression. The results have been consolidated into one single table (above) with the standard errors in parentheses. It should be noted that the full factorial model has been estimated, which includes each independent variable separated being specified along with their interaction with *DIS*. For the purposes of brevity, only the RRR coefficients of interaction variables have been included to avoid extensively long results tables. The full results can be provided upon request. A relative risk ratio (RRR) less than 1 indicates that a firm was more likely to experience less-than-normal volatility, an RRR coefficient of 1 (or close to 1) indicates that the independent variable had no effect on a firm's abnormal return volatility and an RRR coefficient greater than 1 denotes that a firm was more likely to experience abnormal return volatility. Abnormal return volatility (*AVAR–GARCH*) is further classified into three categories, denoting its level: category 1 (low abnormal return volatility), category 2 (moderate abnormal return volatility) and category 3 (high abnormal return volatility). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Appendix 2.2: Robustness Test 2 – Alternate Proxy (*AVAR–GJR–GARCH*) for Abnormal Return Volatility

Model 1: Entire Sample Period

	Standalone SEOs						Restricted SEOs			Combined SEOs								
	Renounceable rights issue			Non-renounceable rights issue			Placement			Placement & non-renounceable rights issue			Placement & SPP			Placement & renounceable rights issue		
	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Variable	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR
AVOL	1.24***	1.48***	1.62**	1.35***	1.42***	1.45***	1.15***	1.18***	1.20***	1.15***	1.29***	1.53***	1.48***	1.61***	1.76***	1 12*	1.26***	1.24**
	(0.10)	(0.22)	(0.32)	(0.08)	(0.10)	(0.11)	(0.06)	(0.07)	(0.07)	(0.05)	(0.07)	(0.12)	(0.08)	(0.11)	(0.14)	(0.07)	(0.11)	(0.11)
DISC	1.11*	0 94	0.83	1.00	1.10	0.96	1.04	1.04	0.77**	1.03	1.08*	1.25***	1.18***	1 23***	1.43***	0.88	0.01	0.07
	(0.07)	(0.13)	(0.10)	(0.08)	(0.12)	(0.17)	(0.06)	(0.10)	(0.10)	(0.03)	(0.05)	(0.09)	(0.06)	(0.09)	(0.16)	(0.24)	(0.02)	(0.32)
ILLIQ	1.04***	1.04***	1.04**	1.02***	1.02***	1.02***	1.01***	1.01***	1.02***	1.01***	1.02***	1.02***	1.01***	1.01***	1.02***	1.01***	1.02***	1.01***
	(0.01)	(0.01)	(0.02)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
BAS	0.78***	0.81	1.04	0.93	1.05	0.84	1.06	1.08	1.02	0.91	1.03	0.89	1.03	1.06	0.93	0.80	0.82	0.96
	(0.05)	(0.11)	(0.12)	(0.07)	(0.11)	(0.13)	(0.03)	(0.06)	(0.11)	(0.06)	(0.09)	(0.17)	(0.04)	(0.08)	(0.14)	(0.12)	(0.27)	(0.31)
MSA	0.99	1.01	0.99	1.00	0.99	0.98	1.01*	1.02**	1.04***	1.00	1.03	0.86***	1.03***	1.04***	1.03	1.01	1.14	0.91
	(0.01)	(0.02)	(0.05)	(0.01)	(0.02)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.04)	(0.01)	(0.01)	(0.03)	(0.02)	(0.11)	(0.22)
CIT	1.02	1 13	0.74	0.99	0.78	0.00***	3.00***	2.09*	1.26	1.07	1.03	0.51	0.86	1.76	0.64	0.47	0.00***	0.00***
	(0.51)	(1.01)	(0.75)	(0.57)	(0.87)	(0.00)	(0.62)	(0.89)	(0.73)	(0.41)	(0.73)	(0.66)	(0.29)	(0.75)	(0.83)	(0.72)	(0.00)	(0.00)
COE	1.04***	1.01	1.02	0.97***	0.96***	0.98	0.99**	0.98***	1.01	1.02*	1.03**	1.10***	0.99	0 97*	0.97	1.04**	1.07**	1.09***
	(0.01)	(0.03)	(0.03)	(0.01)	(0.02)	(0.02)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.03)
MBV	1.58***	1.66***	1.95**	1.14	1.27**	1.42*	1.10**	1.18**	1.22*	0.87*	1.19	1.74**	1.03	1.02	0.86	2.01**	1.99	3.58*
	(0.19)	(0.30)	(0.57)	(0.10)	(0.15)	(0.29)	(0.04)	(0.09)	(0.15)	(0.07)	(0.14)	(0.39)	(0.07)	(0.13)	(0.20)	(0.56)	(1.39)	(2.57)
SIZE	0.89*	0.78	0.75	1.01	0.99	1.07	0.96*	0.87***	0.92	1.27***	1.19**	1.30**	0.90***	0.78***	0.82	1.03	0.96	0.70
	(0.06)	(0.12)	(0.17)	(0.07)	(0.10)	(0.16)	(0.02)	(0.03)	(0.07)	(0.06)	(0.10)	(0.14)	(0.04)	(0.06)	(0.11)	(0.11)	(0.33)	(0.29)
DIS	3.63***	0.86	1.31	3.92***	1.16	0.00***	1.88***	1.97***	3.41***	1.65*	1.96	2.77	1.70***	1.60*	1.10	2.62*	3.59	10.40
	(0.96)	(0.61)	(1.30)	(1.21)	(0.75)	(0.00)	(0.23)	(0.40)	(1.18)	(0.49)	(0.83)	(1.84)	(0.26)	(0.45)	(0.69)	(1.43)	(5.41)	(19.52)
AMV	1.04	1 58**	0.97	1.37**	1.08	0.41*	1.09*	1.41***	1.24*	1.04	1.10	0.96	1.10*	1 16*	1.22	1 94***	1.49	1.35
	(0.13)	(0.30)	(0.31)	(0.17)	(0.29)	(0.19)	(0.05)	(0.10)	(0.16)	(0.11)	(0.14)	(0.26)	(0.06)	(0.10)	(0.23)	(0.39)	(0.63)	(0.64)
Constant	0.09	0.49	1.05	0.05*	0.06	0.00**	0.25**	0.49	0.01***	0.00***	0.00***	0.00***	0.50	3.64	0.20	0.00**	0.00	0.41
	(0.15)	(1.95)	(5.49)	(0.09)	(0.14)	(0.01)	(0.14)	(0.45)	(0.02)	(0.00)	(0.00)	(0.00)	(0.50)	(6.40)	(0.64)	(0.00)	(0.00)	(3.66)

This table provides the regression results for each SEO type during the entire sample period (Model 1). It displays the relative risk ratios (RRR) and standard errors in parentheses of each variable in each *AVAR–GARCH* category. An RRR coefficient of less than 1 indicates that a firm was more likely to experience less-than-normal volatility, an RRR coefficient of 1 (or close to 1) shows that the independent variable had no effect on a firm's abnormal return volatility and an RRR coefficient greater than 1 denotes that a firm was more likely to experience abnormal return volatility. The abnormal return volatility (*AVAR–GARCH*) is classified into three categories: category 1 (low abnormal return volatility), category 2 (moderate abnormal return volatility) and category 3 (high abnormal return volatility). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Appendix 2.2: Robustness Test 2 – Alternate Proxy (*AVAR–GJR–GARCH*) for Abnormal Return Volatility (Continued)

Model 2: Economic Disruptions

	Standalone SEOs						**Restricted SEOs**			**Combined SEOs**								
	Renounceable Rights Issue			**Non-renounceable Rights Issue**			**Placement**			**Placement & Non-renounceable Rights Issue**			**Placement & SPP**			**Placement & Renounceable Rights Issue**		
	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Variable	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR
*AVOL*DIS*	0.65**	0.96	0.73	0.82	1.13	0.88	0.87**	0.85**	0.90	1.51*	1.35	2.09**	0.79**	0.75**	0.71**	20.97**	12.31*	23.43**
	(0.12)	(0.20)	(0.19)	(0.14)	(0.29)	(0.19)	(0.06)	(0.06)	(0.08)	(0.36)	(0.37)	(0.69)	(0.09)	(0.11)	(0.11)	(27.63)	(15.77)	(31.70)
*DISC*DIS*	0.00**	0.00**	0.00	0.01	0.16	18.58	3.41	6.85	0.60	1.14	1.35	0 99	4.61	3.30***	597.18	0.04	0.00***	0.00*
	(0.00)	(0.00)	(0.00)	(0.02)	(1.52)	(68.88)	(2.56)	(9.10)	(1.26)	(0.14)	(0.29)	(0.25)	(7.45)	(6.99)	(308 28)	(0.18)	(0.00)	(0.00)
*ILLIQ*DIS*	1.02	0.98	1.04	1.01	1.02**	0.98***	1.00	1.00	1.01	1.04***	1.07***	0 98	4.06***	9.01***	5.51***	1.62	61.50	15.92**
	(0.04)	(0.05)	(0.05)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)	(0.03)	(1.58)	(4.22)	(3.17)	(9.43)	(5.01)	(1.14)
*BAS*DIS*	1.30	0.96	0.66	0.94	0.72	1.50**	1.05	1.07	0.89	1.08	0.79	0 98	1.07	0.97	1.99**	0.27	0.00***	0.95
	(0.21)	(0.45)	(0.34)	(0.16)	(0.34)	(0.31)	(0.08)	(0.13)	(0.17)	(0.20)	(0.22)	(0.31)	(0.10)	(0.17)	(0.58)	(0.34)	(0.01)	(0.40)
*MSA*DIS*	1.08***	0.86	0.92	1.03	0.69**	1.15*	1.02	1.02	0.99	1.01	1.18**	0.89	0.98	0.96	0.87	1.00	1.00	1.00
	(0.03)	(0.10)	(0.08)	(0.06)	(0.12)	(0.09)	(0.02)	(0.03)	(0.05)	(0.05)	(0.09)	(0.09)	(0.03)	(0.04)	(0.11)	(0.00)	(0.00)	(0.00)
*CIT*DIS*	0.00***	0.00***	0.00***	0.36	0.00***	2.15***	1.22	0.30	0.00***	0.54	0.00***	18.57	0.90	1.32	0.00***	0.00***	0.14	0.05
	(0.00)	(0.00)	(0.00)	(0.45)	(0.00)	(2.14)	(0.57)	(0.35)	(0.00)	(0.67)	(0.00)	(45.24)	(0.67)	(1.15)	(0.00)	(0.00)	(0.25)	(0.10)
*COE*DIS*	1.50*	1.50*	3.05*	1.00	1.00	1.02	1.01	1.03	0.92**	1.07	1.01	1.49**	1.01	1.02	0.97	1.46	1.62***	1.79***
	(0.36)	(0.35)	(1.89)	(0.02)	(0.03)	(0.03)	(0.01)	(0.02)	(0.03)	(0.05)	(0.05)	(0.26)	(0.02)	(0.03)	(0.05)	(0.85)	(5.06)	(8.69)
*MBV*DIS*	2.48**	0.80	0.61	0.70	0.54	5.32***	0.90	0.48***	0.64	0.74	1.85	0.08**	1.00	1.09	2.09**	0.03	0.00***	0.00***
	(0.96)	(0.27)	(0.37)	(0.27)	(0.47)	(2.38)	(0.11)	(0.11)	(0.19)	(0.33)	(0.90)	(0.09)	(0.15)	(0.27)	(0.74)	(0.19)	(0.00)	(0.00)
*SIZE*DIS*	1.92*	1.41	1.08	0.87	0.74	1.85***	1.12**	1.08	0.89	0.86	0.72	0.87	1.30**	1.24	1.06	1.70	0.00***	0.01
	(0.65)	(0.59)	(0.91)	(0.11)	(0.20)	(0.28)	(0.05)	(0.08)	(0.11)	(0.12)	(0.19)	(0.21)	(0.14)	(0.24)	(0.49)	(10.95)	(0.00)	(0.05)
*AMV*DIS*	0.78	0.66	0.43	1.19	1.97	4.53***	0.93	0.98	0.49**	0.80	0.53**	0 56	1.26*	0.94	1.58	0.41**	0.00**	0.21***
	(0.20)	(0.21)	(0.40)	(0.29)	(1.23)	(2.40)	(0.09)	(0.14)	(0.17)	(0.18)	(0.16)	(0.25)	(0.17)	(0.19)	(0.53)	(0.16)	(0.00)	(0.12)

This table presents the regression results for each SEO type during economic disruptions (Model 2), which shows the interactions (in bold) of economic disruptions (*DIS*) with each independent variable as a separate regression, holding all other independent variables constant (a total of 10 independent regressions). The models were executed in this way to prevent the potential for multicollinearity of the *DIS* variable with other instances of *DIS* within the same regression. The results have been consolidated into one single table (above) with the standard errors in parentheses. It should be noted that the full factorial model has been estimated, which includes each independent variable separated being specified along with their interaction with *DIS*. For the purposes of brevity, only the RRR coefficients of interaction variables have been included to avoid extensively long results tables. The full results can be provided upon request. A relative risk ratio (RRR) less than 1 indicates that a firm was more likely to experience less-than-normal volatility, an RRR coefficient of 1 (or close to 1) indicates that the independent variable had no effect on a firm's abnormal return volatility and an RRR coefficient greater than 1 denotes that a firm was more likely to experience abnormal return volatility. Abnormal return volatility (*AVAR–GARCH*) is further classified into three categories, denoting its level: category 1 (low abnormal return volatility), category 2 (moderate abnormal return volatility) and category 3 (high abnormal return volatility). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Appendix 2.3: Robustness Test 3 – Alternate Proxies for Independent Variables

Model 1: Entire Sample Period

	Standalone SEOs						**Restricted SEOs**			**Combined SEOs**								
	Renounceable Rights Issue			**Non-renounceable Rights Issue**			**Placement**			**Placement & Non-renounceable Rights Issue**			**Placement & SPP**			**Placement & Renounceable Rights Issue**		
	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Variable	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR
ATR	1.14***	1.23***	1.28**	1.19***	1.24***	1.26***	1.16***	1.24***	1.26***	1.12***	1.21***	1.32***	1 23***	1.31***	1.38***	1.09**	1 13**	1.21***
	(0.04)	(0.09)	(0.13)	(0.04)	(0.04)	(0.05)	(0.02)	(0.03)	(0.04)	(0.03)	(0.05)	(0.08)	(0.03)	(0.05)	(0.08)	(0.04)	(0.06)	(0.07)
DISC	1.05	0.89	0.81	1.28***	1.47***	1.39**	1.10*	1.09	0.88	1.06**	1.07*	1.30***	1 22***	1.30***	1.66***	1.07	0.01	0.00
	(0.07)	(0.13)	(0.11)	(0.08)	(0.13)	(0.18)	(0.06)	(0.12)	(0.13)	(0.03)	(0.05)	(0.11)	(0.06)	(0.09)	(0.19)	(0.22)	(0.05)	(0.01)
LIQ	0.63***	0.52***	0.50***	0.61***	0.52***	0.59***	0.64***	0.50***	0.47***	0.64***	0.53***	0.45***	0 52***	0.44***	0.38***	0.70***	0 57***	0.56*
	(0.04)	(0.06)	(0.08)	(0.04)	(0.05)	(0.06)	(0.02)	(0.02)	(0.03)	(0.04)	(0.05)	(0.08)	(0.03)	(0.03)	(0.05)	(0.07)	(0.10)	(0.17)
BAS	0.85**	0.86	1.08	0.87**	0.96	0.79	1.07**	1.11*	1.07	1.02	1.19**	1.14	1 14***	1.20**	1.01	1.01	1 19	1.56
	(0.05)	(0.12)	(0.16)	(0.06)	(0.10)	(0.13)	(0.04)	(0.06)	(0.10)	(0.07)	(0.10)	(0.19)	(0.05)	(0.09)	(0.14)	(0.14)	(0.34)	(0.69)
MSA	1.00	1.01	0.98	0.99	0.98	0.97	1.02***	1.03***	1.05***	1.02	1.06***	0.89**	1.04***	1.04***	1.01	1.02	1 15	0.80
	(0.01)	(0.03)	(0.06)	(0.01)	(0.02)	(0.04)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.04)	(0.01)	(0.02)	(0.03)	(0.02)	(0.13)	(0.21)
CIT	1.09	1.16	0.95	1.46	1.63	0.00***	3.18***	1.98	0.86	1.24	1.34	0.55	0.73	1.52	0.48	0.34	0.00***	0.00***
	(0.56)	(0.97)	(0.96)	(0.83)	(1.74)	(0.00)	(0.67)	(0.95)	(0.55)	(0.48)	(0.91)	(0.83)	(0.26)	(0.67)	(0.72)	(0.49)	(0.00)	(0.00)
COE	1.03**	1.00	1.02	0.96***	0.95***	0.97	0.99**	0.98***	1.01	1.00	1.00	1.07**	0 99	0.97*	0.98	1.02	1.04	1.05
	(0.02)	(0.04)	(0.04)	(0.01)	(0.01)	(0.02)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.04)
MBV	1.80***	2.11***	2.56***	1.34***	1.53***	1.49*	1.30***	1.48***	1.48***	1.10	1.42***	2.27***	1 31***	1.41**	1.39	2.27***	1.83	18.10***
	(0.25)	(0.48)	(0.86)	(0.14)	(0.22)	(0.35)	(0.06)	(0.12)	(0.18)	(0.09)	(0.18)	(0.61)	(0.10)	(0.19)	(0.34)	(0.66)	(1.09)	(19.17)
SIZE	0.89*	0.80	0.75	1.00	0.99	1.07	0.96*	0.88***	0.90	1.27***	1.21**	1.31**	0.89***	0.78***	0.82	1.02	0 98	0.69
	(0.06)	(0.13)	(0.17)	(0.07)	(0.10)	(0.16)	(0.02)	(0.03)	(0.06)	(0.06)	(0.10)	(0.14)	(0.04)	(0.06)	(0.11)	(0.11)	(0.33)	(0.29)
DIS	3.35***	1.07	2.07	3.81***	0.96	0.00***	1.95***	2.14***	3.63***	2.41***	3.08**	6.69***	1 55***	1.29	0.70	4.67***	7 34	181.11***
	(0.93)	(0.78)	(1.82)	(1.10)	(0.61)	(0.00)	(0.25)	(0.46)	(1.29)	(0.73)	(1.35)	(4.73)	(0.26)	(0.40)	(0.50)	(2.62)	(11.78)	(315.77)
AMV	0.99	1.50**	0.93	1.19	0.90	0.36**	1.03	1.34***	1.19	1.05	1.13	0.93	0 97	1.02	1.10	1.97***	1.47	1.64
	(0.13)	(0.31)	(0.29)	(0.15)	(0.26)	(0.17)	(0.05)	(0.10)	(0.16)	(0.11)	(0.15)	(0.21)	(0.06)	(0.09)	(0.21)	(0.39)	(0.62)	(1.15)
Constant	3.33	4.71	5.09	0.44	0.63	0.15	4.05***	12.71***	2.35	0.29*	1.89	0.68	59.08***	187.07***	54.34**	1.23	3 54	3.78**
	(3.56)	(10.23)	(13.15)	(0.39)	(0.80)	(0.31)	(1.39)	(6.95)	(2.11)	(0.21)	(2.01)	(1.65)	(39.93)	(197.86)	(90.32)	(1.59)	(9.25)	(2.58)

Note. This table provides the regression results for each SEO type during the entire sample period (Model 1). It displays the relative risk ratios (RRR) and standard errors in parentheses of each variable in each *AVAR–GARCH* category. An RRR coefficient of less than 1 indicates that a firm was more likely to experience less-than-normal volatility, an RRR coefficient of 1 (or close to 1) shows that the independent variable had no effect on a firm's abnormal return volatility and an RRR coefficient greater than 1 denotes that a firm was more likely to experience abnormal return volatility. The abnormal return volatility (*AVAR–GARCH*) is classified into three categories: category 1 (low abnormal return volatility), category 2 (moderate abnormal return volatility) and category 3 (high abnormal return volatility). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Appendix 2.3 Robustness Test 3 – Alternate Proxies for Independent Variables (Continued)

Model 2: Economic Disruptions

	Standalone SEOs						Restricted SEOs			Combined SEOs								
	Renounceable Rights Issue			Non-renounceable Rights Issue			Placement			Placement & Non-renounceable Rights Issue			Placement & SPP			Placement & Renounceable Rights Issue		
	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Variable	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR
*ATR*DIS*	0.96	1.25	1 37	0.88**	0.95	0.86**	0.97	0 98	1.02	1 32	1.15	1.53	0.84***	0.81***	0.77***	1.41**	1.31*	1.25
	(0.11)	(0.22)	(0.28)	(0.05)	(0.08)	(0.06)	(0.05)	(0.06)	(0.08)	(0.34)	(0.28)	(0.46)	(0.03)	(0.05)	(0.06)	(0.21)	(0.19)	(0.20)
*DISC*DIS*	0.00***	0.00*	0.00	0.02	1.99	1.39***	2.29	6.76	0.37	1.08	1.16	0.91	1.13	354.65**	149.00	0.04	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.07)	(17.85)	(0.76)	(1.71)	(8.79)	(0.77)	(0.13)	(0.25)	(0.29)	(1.94)	(810.35)	(799.28)	(0.23)	(0.00)	(0.00)
*LIQ*DIS*	1.22	1.06	0 92	0.88	0.83	1.10	1.06*	0 99	0.96	0 94	0.86	0.97	0.71***	0.49***	0.31***	0.82	0.08**	0.04***
	(0.16)	(0.20)	(0.21)	(0.07)	(0.15)	(0.15)	(0.04)	(0.05)	(0.08)	(0.09)	(0.14)	(0.13)	(0.07)	(0.08)	(0.12)	(0.38)	(0.09)	(0.04)
*BAS*DIS*	1.17	0.76	0.43**	0.92	0.80	2.90***	1.07	1.05	0.92	1.02	0.85	0.87	0.97	0.84	1.64	0.25	0.00***	0.84
	(0.19)	(0.44)	(0.15)	(0.16)	(0.38)	(0.79)	(0.09)	(0.13)	(0.17)	(0.18)	(0.20)	(0.27)	(0.10)	(0.16)	(0.54)	(0.30)	(0.00)	(0.52)
*MSA*DIS*	1.07**	0.83	0.86	0.97	0.62*	1.08	1.00	0 98	0.96	0 99	1.10	0.87	0.98	0.97	0.90	1.00	1.00	1.00
	(0.03)	(0.12)	(0.09)	(0.05)	(0.17)	(0.08)	(0.02)	(0.04)	(0.05)	(0.05)	(0.08)	(0.10)	(0.03)	(0.05)	(0.12)	(0.00)	(0.00)	(0.00)
*CIT*DIS*	0.00***	0.00***	0.00***	0.20	0.00***	5.11***	0.80	0 22	0.00***	0 50	0.00***	19.02	0.91	1.11	0.00***	0.00***	0.08	0.00**
	(0.00)	(0.00)	(0.00)	(0.26)	(0.00)	(5.20)	(0.38)	(0.26)	(0.00)	(0.57)	(0.00)	(97.54)	(0.69)	(1.03)	(0.00)	(0.00)	(0.15)	(0.00)
*COE*DIS*	1.41	1.25	2.04	0.99	0.99	1.03	0.99	1.00	0.90***	1.07	0.97	1.63**	0.98	0.98	0.92	1.43	3.50***	1.80***
	(0.40)	(0.25)	(1.07)	(0.02)	(0.03)	(0.03)	(0.01)	(0.02)	(0.03)	(0.05)	(0.05)	(0.33)	(0.02)	(0.03)	(0.05)	(0.89)	(1.14)	(0.94)
*MBV*DIS*	2.03*	0.72	0.64	0.64	0.61	3.06*	1.15	0.68*	1.03	0.71	2.84*	0.06*	1.36*	1.61*	4.28***	0.03	0.00***	0.00***
	(0.85)	(0.28)	(0.42)	(0.24)	(0.52)	(1.81)	(0.15)	(0.15)	(0.29)	(0.32)	(1.60)	(0.10)	(0.24)	(0.46)	(2.10)	(0.19)	(0.00)	(0.00)
*SIZE*DIS*	1.95**	1.44	1.08	0.87	0.74	1.85***	1.12**	1.08	0.92	0.86	0.72	0.87	1.27**	1.23	1.06	0.56	0.00***	0.01
	(0.65)	(0.59)	(0.91)	(0.11)	(0.20)	(0.28)	(0.05)	(0.08)	(0.11)	(0.12)	(0.19)	(0.21)	(0.14)	(0.24)	(0.49)	(10.95)	(0.00)	(0.05)
*AMV*DIS*	0.75	0.68	0.49	1.04	1.84	6.99***	0.86	0.87	0.42**	0.82	0.62	0.56	1.29*	0.96	1.52	0.41**	0.00**	0.03**
	(0.20)	(0.22)	(0.45)	(0.27)	(1.09)	(3.44)	(0.09)	(0.12)	(0.16)	(0.19)	(0.19)	(0.24)	(0.17)	(0.19)	(0.49)	(0.16)	(0.00)	(0.05)

This table presents the regression results for each SEO type during economic disruptions (Model 2), which shows the interactions (in bold) of economic disruptions (*DIS*) with each independent variable as a separate regression, holding all other independent variables constant (a total of 10 independent regressions). The models were executed in this way to prevent the potential for multicollinearity of the *DIS* variable with other instances of *DIS* within the same regression. The results have been consolidated into one single table (above) with the standard errors in parentheses. It should be noted that the full factorial model has been estimated, which includes each independent variable separated being specified along with their interaction with *DIS*. For the purposes of brevity, only the RRR coefficients of interaction variables have been included to avoid extensively long results tables. The full results can be provided upon request. A relative risk ratio (RRR) less than 1 indicates that a firm was more likely to experience less-than-normal volatility, an RRR coefficient of 1 (or close to 1) indicates that the independent variable had no effect on a firm's abnormal return volatility and an RRR coefficient greater than 1 denotes that a firm was more likely to experience abnormal return volatility. Abnormal return volatility (*AVAR–GARCH*) is further classified into three categories, denoting its level: category 1 (low abnormal return volatility), category 2 (moderate abnormal return volatility) and category 3 (high abnormal return volatility). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Appendix 3: Robustness Tests by Sector

Appendix 3.1: Robustness Test 1 – Robust Standard Errors

Model 1: Entire Sample Period

	High-performing Sectors								
	Health Care			Information Technology			Energy		
	1	2	3	1	2	3	1	2	3
Variable	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR
AVOL	1.32***	1.41***	1.37***	1.59***	1.87***	1.94***	1.33***	1.42***	1.65***
	(0.10)	(0.12)	(0.12)	(0.17)	(0.26)	(0.40)	(0.15)	(0.15)	(0.24)
DISC	0.99	0.96	1.02	1.01	1.02	1.02	1.00	1.00	0.98
	(0.01)	(0.04)	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.01)
ILLIQ	1.02***	1.02***	1.02***	1.01***	1.01***	1.02***	1.01**	1.01**	1.01**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
BAS	1.19**	1.17	0.77	0.87	0.85	1.20	0.83*	1.02	0.43**
	(0.09)	(0.14)	(0.19)	(0.11)	(0.15)	(0.41)	(0.09)	(0.13)	(0.14)
MSA	1.05***	0.98	1.06	1.04	0.99	0.73	0.99	1.01	0.90**
	(0.02)	(0.03)	(0.04)	(0.04)	(0.05)	(0.18)	(0.01)	(0.02)	(0.04)
CIT	1.40	5.77**	0.00***	0.76	0.00***	0.00***	0.62	0.00***	0.00***
	(0.85)	(3.94)	(0.00)	(0.49)	(0.00)	(0.00)	(1.07)	(0.00)	(0.00)
COE	0.99	1.00	0.98	0.97*	0.98	0.94	1.02	0.98	1.11*
	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.05)	(0.02)	(0.02)	(0.06)
MBV	0.99	1.56**	0.88	1.52***	1.61***	2.89***	1.03	1.20	0.60
	(0.14)	(0.34)	(0.33)	(0.20)	(0.28)	(0.79)	(0.20)	(0.45)	(0.44)
SIZE	1.04	0.88	0.95	1.08	1.14	0.64	0.94	0.68***	1.92**
	(0.08)	(0.11)	(0.19)	(0.11)	(0.17)	(0.24)	(0.08)	(0.09)	(0.60)
DIS	1.21	0.71	4.64	0.89	0.48	0.90	1.67	2.82**	2.61
	(0.37)	(0.41)	(5.64)	(0.43)	(0.32)	(1.01)	(0.61)	(1.37)	(2.10)
AMV	1.07	1.51**	0.78	1.34**	1.25	1.65***	1.08	1.56*	1.51
	(0.12)	(0.26)	(0.26)	(0.16)	(0.22)	(0.30)	(0.20)	(0.39)	(0.54)
Constant	0.04*	0.14	0.00	0.00**	0.00**	20.38	0.10	78.21	0.00***
	(0.08)	(0.38)	(0.02)	(0.01)	(0.00)	(179.07)	(0.22)	(223.21)	(0.00)

Note. This table provides the regression results for each sector during the entire sample period (Model 1). It displays the relative risk ratios (RRR) and standard errors in parentheses of each variable in each *AVAR–GARCH* category. An RRR coefficient of less than 1 indicates that a firm was more likely to experience less-than-normal volatility, an RRR coefficient of 1 (or close to 1) shows that the independent variable had no effect on a firm's abnormal return volatility and an RRR coefficient greater than 1 denotes that a firm was more likely to experience abnormal return volatility. The abnormal return volatility (*AVAR–GARCH*) is classified into three categories: category 1 (low abnormal return volatility), category 2 (moderate abnormal return volatility) and category 3 (high abnormal return volatility). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Model 1: Entire Sample Period (Continued)

	Moderate-performing Sectors															Low-performing Sector		
	Consumer Discretionary			Financials			Industrials			Materials			Consumer Staples			Real Estate		
	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Variable	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR
AVOL	1.08	1.12*	1.13*	1.25*	1.34	1.35	1 21*	1.27*	1.36**	1.26***	1.40***	1.48***	1.19**	1.31*	2.21***	1.37***	1.52***	1.48***
	(0.05)	(0.07)	(0.07)	(0.17)	(0.27)	(0.28)	(0.14)	(0.16)	(0.19)	(0.05)	(0.09)	(0.11)	(0.10)	(0.19)	(0.50)	(0.09)	(0.11)	(0.12)
DISC	1.00	0.96***	1.00	0.93	1.09	0.10	0 99	0.47	0.22	1.01	0.98	1.02***	0.89	1.07	1.11	1.01	0.99*	0.95
	(0.00)	(0.01)	(0.01)	(0.21)	(0.36)	(0.17)	(0.01)	(0.34)	(0.31)	(0.00)	(0.02)	(0.01)	(0.08)	(0.22)	(0.19)	(0.00)	(0.01)	(0.24)
ILLIQ	1.02***	1.02***	1.02***	1.00	1.00	1.01**	1.02***	1.01	1.02**	1.02***	1.02***	1.03***	1.17***	1.15**	1.21***	1.06***	1.06***	1.06***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.05)	(0.06)	(0.08)	(0.02)	(0.02)	(0.02)
BAS	0.94	1.21*	1.38*	0.98	1.30***	1.00	0 90	0.93	1.21	0.85***	0.86**	0.79**	0.89	1.11	0.74	1.09	1.03	1.61*
	(0.05)	(0.12)	(0.24)	(0.06)	(0.13)	(0.18)	(0.06)	(0.11)	(0.21)	(0.03)	(0.06)	(0.08)	(0.10)	(0.26)	(0.31)	(0.09)	(0.15)	(0.44)
MSA	1.00	0.96	0.92	1.00	0.97	1.03	1.00	0.98	1.02	1.02**	1.03***	1.02	1.01	0.71*	0.51**	0.99	0.95	1.15**
	(0.02)	(0.04)	(0.08)	(0.02)	(0.04)	(0.04)	(0.01)	(0.03)	(0.07)	(0.01)	(0.01)	(0.01)	(0.07)	(0.13)	(0.17)	(0.02)	(0.05)	(0.07)
CIT	1.16	4.15**	2.69	2.32***	1.65	0.00***	1 18	1.19	1.30	1.89**	1.29	1.87	1.81	0.00***	0.00***	1.16	4.81**	0.00***
	(0.52)	(2.34)	(2.71)	(0.75)	(1.21)	(0.00)	(0.51)	(0.94)	(1.24)	(0.49)	(0.63)	(1.17)	(1.18)	(0.00)	(0.00)	(0.53)	(3.20)	(0.00)
COE	0.99	0.98***	0.99	1.03	1.07**	1.00	0 99	0.99	0.95	0.99***	0.98***	1.02	1.00	1.01	0.91*	1.08***	1.20***	1.06
	(0.00)	(0.01)	(0.01)	(0.02)	(0.03)	(0.04)	(0.01)	(0.03)	(0.03)	(0.00)	(0.01)	(0.01)	(0.01)	(0.03)	(0.05)	(0.02)	(0.06)	(0.10)
MBV	1.07	1.18	1.14	1.23*	1.53	1.15	1 23**	1.12	0.98	0.97	0.98	1.15	1.00	0.39	4.11	0.75	1.23	0.19***
	(0.08)	(0.22)	(0.25)	(0.15)	(0.44)	(0.49)	(0.11)	(0.22)	(0.25)	(0.05)	(0.08)	(0.15)	(0.35)	(0.26)	(3.60)	(0.14)	(0.43)	(0.10)
SIZE	1.08	1.04	1.08	0.89**	0.89	0.84	0.79**	0.79	0.52**	1.23***	1.20***	1.25***	1.01	0.65	7.02***	1.01	1.31	0.58
	(0.08)	(0.14)	(0.29)	(0.05)	(0.11)	(0.13)	(0.08)	(0.16)	(0.17)	(0.04)	(0.06)	(0.10)	(0.21)	(0.31)	(4.50)	(0.09)	(0.31)	(0.29)
DIS	1.30	1.01	0.00***	2.80***	2.78**	2.71	5 30***	5.01***	4.96**	1.39*	0.94	1.21	1.53	1.51	0.89	2.39***	1.63	0.00***
	(0.32)	(0.50)	(0.00)	(0.56)	(1.14)	(2.15)	(1.24)	(2.45)	(3.20)	(0.24)	(0.27)	(0.53)	(0.74)	(1.18)	(1.17)	(0.55)	(1.25)	(0.00)
AMV	1.12	1.82***	1.23	1.08	1.29**	1.08	1.05	1.35*	1.23	1.09	1.11	0.98	1.10	1.34**	0.71	0.95	1.33*	1.29
	(0.12)	(0.33)	(0.57)	(0.09)	(0.14)	(0.28)	(0.10)	(0.21)	(0.44)	(0.07)	(0.11)	(0.14)	(0.15)	(0.19)	(0.31)	(0.10)	(0.20)	(0.55)
Constant	0.02**	0.02	0.01	0.23	0.03	0.19	7.81	2.21	25.71	0.00***	0.00***	0.00***	0.04	6.56	0.00***	0.01**	0.00***	24.75
	(0.03)	(0.05)	(0.03)	(0.36)	(0.09)	(0.82)	(18.81)	(10.82)	(18.49)	(0.00)	(0.00)	(0.00)	(0.16)	(6.35)	(0.00)	(0.01)	(0.00)	(312.92)

Note. This table provides the regression results for each sector during the entire sample period (Model 1). It displays the relative risk ratios (RRR) and standard errors in parentheses of each variable in each *AVAR–GARCH* category. An RRR coefficient of less than 1 indicates that a firm was more likely to experience less-than-normal volatility, an RRR coefficient of 1 (or close to 1) shows that the independent variable had no effect on a firm's abnormal return volatility and an RRR coefficient greater than 1 denotes that a firm was more likely to experience abnormal return volatility. The abnormal return volatility (*AVAR–GARCH*) is classified into three categories: category 1 (low abnormal return volatility), category 2 (moderate abnormal return volatility) and category 3 (high abnormal return volatility). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Appendix 3.1: Robustness Test 1 – Robust Standard Errors (Continued)

Model 2: Economic Disruptions

	High-performing Sectors								
	Health Care			**Information Technology**			**Energy**		
	1	2	3	1	2	3	1	2	3
Variable	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR
*AVOL*DIS*	0.69***	0.71***	0.65***	0.83	1.11	1.01	0.82	0.95	3.71***
	(0.06)	(0.06)	(0.06)	(0.23)	(0.47)	(0.51)	(0.26)	(0.28)	(1.41)
*DISC*DIS*	0.00	0.00*	4.96*	0.98	0.92**	1.08	0.90	1.07	0.97
	(0.00)	(0.00)	(2.40)	(0.02)	(0.03)	(0.07)	(0.10)	(0.18)	(0.20)
*ILLIQ*DIS*	1.46	2.40**	7.41***	69.19**	66.16**	932.52**	1.03**	1.05***	1.00
	(0.78)	(1.05)	(3.22)	(118.06)	(120.34)	(277.32)	(0.01)	(0.02)	(0.03)
*BAS*DIS*	1.06	1.58	1.10	1.24	0.59	0.83	0.68	0.65*	1.63
	(0.17)	(0.57)	(0.55)	(0.28)	(0.24)	(0.37)	(0.22)	(0.15)	(0.82)
*MSA*DIS*	1.18*	1.21*	0.84	0.92	0.76***	0.83	0.88	1.13	0.91
	(0.10)	(0.14)	(0.13)	(0.08)	(0.07)	(0.27)	(0.14)	(0.27)	(0.26)
*CIT*DIS*	2.07	0.00***	1.43	1.39	0.22	26.81*	0.62	0.00***	0.00***
	(3.03)	(0.00)	(2.09)	(2.49)	(0.27)	(52.65)	(1.07)	(0.00)	(0.00)
*COE*DIS*	1.05	1.11	1.03	1.11***	0.31	0.00***	0.95	1.06	0.87
	(0.06)	(0.14)	(0.20)	(0.04)	(0.23)	(0.00)	(0.08)	(0.14)	(0.19)
*MBV*DIS*	0.74	0.33	0.69	0.91	0.37	0.63	0.00*	1.74	682.98
	(0.45)	(0.32)	(1.19)	(0.34)	(0.49)	(0.46)	(0.01)	(5.14)	(2.88)
*SIZE*DIS*	1.46*	1.43	0.01	0.69	0.58	0.81	1.21	0.81	1.27
	(0.33)	(0.51)	(0.05)	(0.29)	(0.47)	(0.64)	(0.34)	(0.33)	(0.67)
*AMV*DIS*	1.14	1.83*	0.16***	1.50	1.87	1.78	0.93	1.27	1.20
	(0.27)	(0.66)	(0.10)	(0.48)	(0.84)	(1.35)	(0.58)	(0.83)	(0.90)

Note. This table presents the regression results for each sector during economic disruptions (Model 2), which shows the interactions (in bold) of economic disruptions (*DIS*) with each independent variable as a separate regression, holding all other independent variables constant (a total of 10 independent regressions). The models were executed in this way to prevent the potential for multicollinearity of the *DIS* variable with other instances of *DIS* within the same regression. The results have been consolidated into one single table (above) with the standard errors in parentheses. It should be noted that the full factorial model has been estimated, which includes each independent variable separated being specified along with their interaction with *DIS*. For the purposes of brevity, only the RRR coefficients of interaction variables have been included to avoid extensively long results tables. The full results can be provided upon request. A relative risk ratio (RRR) less than 1 indicates that a firm was more likely to experience less-than-normal volatility, an RRR coefficient of 1 (or close to 1) indicates that the independent variable had no effect on a firm's abnormal return volatility and an RRR coefficient greater than 1 denotes that a firm was more likely to experience abnormal return volatility. Abnormal return volatility (*AVAR–GARCH*) is further classified into three categories, denoting its level: category 1 (low abnormal return volatility), category 2 (moderate abnormal return volatility) and category 3 (high abnormal return volatility). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Model 2: Economic Disruptions (Continued)

	Moderate-performing Sectors														
	Consumer Discretionary			**Financials**			**Industrials**			**Materials**			**Consumer Staples**		
	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Variable	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR
*AVOL*DIS*	1.20*	1.21*	0.99	1.04	1.16	1.34	1.77**	1.32	3.38***	1.77**	1.32	3.38***	1.20	1.08	14.26**
	(0.12)	(0.13)	(0.09)	(0.24)	(0.39)	(0.56)	(0.49)	(0.43)	(1.31)	(0.49)	(0.43)	(1.31)	(0.35)	(0.35)	(16.99)
*DISC*DIS*	0.02	207.29	0.02	33.41**	205.89**	3.40	0.82	45.04	79.22	0.82	45.04	79.22	0.00	0.30	0.09
	(0.05)	(788.76)	(0.06)	(46.38)	(461.43)	(25.94)	(1.12)	(128.96)	(308.93)	(1.12)	(128.96)	(308.93)	(0.01)	(3.35)	(0.65)
*ILLIQ*DIS*	2.63***	7.83***	1.62*	4.51**	3.12	2.77	1.18	2.02*	1.49	1.18	2.02*	1.49	0.93	1.04	0.93
	(0.92)	(4.54)	(0.46)	(3.23)	(2.86)	(2.63)	(0.43)	(0.83)	(0.59)	(0.43)	(0.83)	(0.59)	(0.09)	(0.11)	(0.12)
*BAS*DIS*	0.98	1.00	0.70**	0.95	0.72*	0.74	0.89	0.81	0.74	0.89	0.81	0.74	1.13	1.67	1.81
	(0.15)	(0.30)	(0.12)	(0.13)	(0.14)	(0.33)	(0.13)	(0.24)	(0.31)	(0.13)	(0.24)	(0.31)	(0.27)	(0.58)	(1.44)
*MSA*DIS*	0.92	1.20	1.11	1.04	1.02	1.15	1.00	0.84***	0.71**	1.00	0.84***	0.71**	0.97	0.86	1.35
	(0.09)	(0.23)	(0.15)	(0.04)	(0.08)	(0.13)	(0.03)	(0.06)	(0.10)	(0.03)	(0.06)	(0.10)	(0.23)	(0.36)	(0.69)
*CIT*DIS*	0.00***	6.26	0.51	1.10	0.60	0.02***	0.97	0.44	0.00***	0.97	0.44	0.00***	7.09	4.08	73.50
	(0.00)	(9.65)	(0.66)	(0.73)	(0.88)	(0.02)	(0.82)	(0.68)	(0.00)	(0.82)	(0.68)	(0.00)	(13.71)	(8.54)	(368.99)
*COE*DIS*	1.06	0.84	1.06*	1.13**	1.18**	1.26***	0.97	1.00	0.87*	0.97	1.00	0.87*	1.01	0.97	0.88
	(0.05)	(0.13)	(0.04)	(0.06)	(0.08)	(0.11)	(0.02)	(0.05)	(0.07)	(0.02)	(0.05)	(0.07)	(0.05)	(0.06)	(0.12)
*MBV*DIS*	1.10	0.77	0.66	0.78	1.03	0.64	1.73***	1.25	0.39	1.73***	1.25	0.39	0.61	0.48	0.00***
	(0.31)	(0.46)	(0.22)	(0.21)	(0.53)	(0.54)	(0.36)	(0.58)	(0.28)	(0.36)	(0.58)	(0.28)	(0.47)	(0.55)	(0.00)
*SIZE*DIS*	0.26**	0.53	0.80	1.25*	1.30	1.12	1.54*	0.73	0.60	1.54*	0.73	0.60	1.28	1.05	2.35
	(0.15)	(0.27)	(0.35)	(0.16)	(0.28)	(0.37)	(0.39)	(0.37)	(0.31)	(0.39)	(0.37)	(0.31)	(0.68)	(0.97)	(2.45)
*AMV*DIS*	0.78	0.64	0.77	1.11	0.64**	0.23***	0.76	0.67	1.32	0.76	0.67	1.32	0.52**	2.05	0.44
	(0.17)	(0.22)	(0.38)	(0.21)	(0.14)	(0.10)	(0.15)	(0.21)	(0.79)	(0.15)	(0.21)	(0.79)	(0.16)	(0.93)	(0.49)

Note. This table presents the regression results for each sector during economic disruptions (Model 2), which shows the interactions (in bold) of economic disruptions (*DIS*) with each independent variable as a separate regression, holding all other independent variables constant (a total of 10 independent regressions). The models were executed in this way to prevent the potential for multicollinearity of the *DIS* variable with other instances of *DIS* within the same regression. The results have been consolidated into one single table (above) with the standard errors in parentheses. It should be noted that the full factorial model has been estimated, which includes each independent variable separated being specified along with their interaction with *DIS*. For the purposes of brevity, only the RRR coefficients of interaction variables have been included to avoid extensively long results tables. The full results can be provided upon request. A relative risk ratio (RRR) less than 1 indicates that a firm was more likely to experience less-than-normal volatility, an RRR coefficient of 1 (or close to 1) indicates that the independent variable had no effect on a firm's abnormal return volatility and an RRR coefficient greater than 1 denotes that a firm was more likely to experience abnormal return volatility. Abnormal return volatility (*AVAR–GARCH*) is further classified into three categories, denoting its level: category 1 (low abnormal return volatility), category 2 (moderate abnormal return volatility) and category 3 (high abnormal return volatility). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Appendix 3.2: Robustness Test 2 – Alternate Proxy for Abnormal Return Volatility (*AVAR–GJR–GARCH*)

Model 1: Entire Sample Period

	High-performing Sectors								
	Health Care			Information Technology			Energy		
	1	2	3	1	2	3	1	2	3
Variable	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR
AVOL	1.32***	1.41***	1.37***	1.59***	1.87***	1.94***	1.33***	1.42***	1.65***
	(0.10)	(0.12)	(0.12)	(0.17)	(0.26)	(0.40)	(0.15)	(0.15)	(0.24)
DISC	0.99	0.96	1.02	1.01	1.02	1.02	1.00	1.00	0.98
	(0.01)	(0.04)	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.01)
ILLIQ	1.02***	1.02***	1.02***	1.01***	1.01***	1.02***	1.01**	1.01**	1.01**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
BAS	1.19**	1.17	0.77	0.87	0.85	1.20	0.83*	1.02	0.43**
	(0.09)	(0.14)	(0.19)	(0.11)	(0.15)	(0.41)	(0.09)	(0.13)	(0.14)
MSA	1.05***	0.98	1.06	1.04	0.99	0.73	0.99	1.01	0.90**
	(0.02)	(0.03)	(0.04)	(0.04)	(0.05)	(0.18)	(0.01)	(0.02)	(0.04)
CIT	1.40	5.77**	0.00***	0.76	0.00***	0.00***	0.62	0.00***	0.00***
	(0.85)	(3.94)	(0.00)	(0.49)	(0.00)	(0.00)	(1.07)	(0.00)	(0.00)
COE	0.99	1.00	0.98	0.97*	0.98	0.94	1.02	0.98	1.11*
	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.05)	(0.02)	(0.02)	(0.06)
MBV	0.99	1.56**	0.88	1.52***	1.61***	2.89***	1.03	1.20	0.60
	(0.14)	(0.34)	(0.33)	(0.20)	(0.28)	(0.79)	(0.20)	(0.45)	(0.44)
SIZE	1.04	0.88	0.95	1.08	1.14	0.64	0.94	0.68***	1.92**
	(0.08)	(0.11)	(0.19)	(0.11)	(0.17)	(0.24)	(0.08)	(0.09)	(0.60)
DIS	1.21	0.71	4.64	0.89	0.48	0.90	1.67	2.82**	2.61
	(0.37)	(0.41)	(5.64)	(0.43)	(0.32)	(1.01)	(0.61)	(1.37)	(2.10)
AMV	1.07	1.51**	0.78	1.34**	1.25	1.65***	1.08	1.56*	1.51
	(0.12)	(0.26)	(0.26)	(0.16)	(0.22)	(0.30)	(0.20)	(0.39)	(0.54)
Constant	0.04*	0.14	0.00	0.00**	0.00**	20.38	0.10	78.21	0.00***
	(0.08)	(0.38)	(0.02)	(0.01)	(0.00)	(179.07)	(0.22)	(223.21)	(0.00)

Note. This table provides the regression results for each sector during the entire sample period (Model 1). It displays the relative risk ratios (RRR) and standard errors in parentheses of each variable in each *AVAR–GARCH* category. An RRR coefficient of less than 1 indicates that a firm was more likely to experience less-than-normal volatility, an RRR coefficient of 1 (or close to 1) shows that the independent variable had no effect on a firm's abnormal return volatility and an RRR coefficient greater than 1 denotes that a firm was more likely to experience abnormal return volatility. The abnormal return volatility (*AVAR–GARCH*) is classified into three categories: category 1 (low abnormal return volatility), category 2 (moderate abnormal return volatility) and category 3 (high abnormal return volatility). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Model 1: Entire Sample Period (Continued)

	Moderate-performing Sectors															Low-performing Sector		
	Consumer Discretionary			Financials			Industrials			Materials			Consumer Staples			Real Estate		
	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Variable	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR
AVOL	1.08	1.12*	1.13*	1.25*	1.34	1.35	1.21*	1.27*	1.36**	1.26***	1.40***	1.48***	1.19**	1.31*	2.21***	1.37***	1.52***	1.48***
	(0.05)	(0.07)	(0.07)	(0.17)	(0.27)	(0.28)	(0.14)	(0.16)	(0.19)	(0.05)	(0.09)	(0.11)	(0.10)	(0.19)	(0.50)	(0.09)	(0.11)	(0.12)
DISC	1.00	0.96***	1.00	0.93	1.09	0.10	0.99	0.47	0.22	1.01	0.98	1.02***	0.89	1.07	1.11	1.01	0.99*	0.95
	(0.00)	(0.01)	(0.01)	(0.21)	(0.36)	(0.17)	(0.01)	(0.34)	(0.31)	(0.00)	(0.02)	(0.01)	(0.08)	(0.22)	(0.19)	(0.00)	(0.01)	(0.24)
ILLIQ	1.02***	1.02***	1.02***	1.00	1.00	1.01**	1.02***	1.01	1.02**	1.02***	1.02***	1.03***	1.17***	1.15**	1.21***	1.06***	1.06***	1.06***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.05)	(0.06)	(0.08)	(0.02)	(0.02)	(0.02)
BAS	0.94	1.21*	1.38*	0.98	1.30***	1.00	0.90	0.93	1.21	0.85***	0.86**	0.79**	0.89	1.11	0.74	1.09	1.03	1.61*
	(0.05)	(0.12)	(0.24)	(0.06)	(0.13)	(0.18)	(0.06)	(0.11)	(0.21)	(0.03)	(0.06)	(0.08)	(0.10)	(0.26)	(0.31)	(0.09)	(0.15)	(0.44)
MSA	1.00	0.96	0.92	1.00	0.97	1.03	1.00	0.98	1.02	1.02**	1.03***	1.02	1.01	0.71*	0.51**	0.99	0.95	1.15**
	(0.02)	(0.04)	(0.08)	(0.02)	(0.04)	(0.04)	(0.01)	(0.03)	(0.07)	(0.01)	(0.01)	(0.01)	(0.07)	(0.13)	(0.17)	(0.02)	(0.05)	(0.07)
CIT	1.16	4.15**	2.69	2.32***	1.65	0.00***	1.18	1.19	1.30	1.89**	1.29	1.87	1.81	0.00***	0.00***	1.16	4.81**	0.00***
	(0.52)	(2.34)	(2.71)	(0.75)	(1.21)	(0.00)	(0.51)	(0.94)	(1.24)	(0.49)	(0.63)	(1.17)	(1.18)	(0.00)	(0.00)	(0.53)	(3.20)	(0.00)
COE	0.99	0.98***	0.99	1.03	1.07**	1.00	0.99	0.99	0.95	0.99***	0.98***	1.02	1.00	1.01	0.91*	1.08***	1.20***	1.06
	(0.00)	(0.01)	(0.01)	(0.02)	(0.03)	(0.04)	(0.01)	(0.03)	(0.03)	(0.00)	(0.01)	(0.01)	(0.01)	(0.03)	(0.05)	(0.02)	(0.06)	(0.10)
MBV	1.07	1.18	1.14	1.23*	1.53	1.15	1.23**	1.12	0.98	0.97	0.98	1.15	1.00	0.39	4.11	0.75	1.23	0.19***
	(0.08)	(0.22)	(0.25)	(0.15)	(0.44)	(0.49)	(0.11)	(0.22)	(0.25)	(0.05)	(0.08)	(0.15)	(0.35)	(0.26)	(3.60)	(0.14)	(0.43)	(0.10)
SIZE	1.08	1.04	1.08	0.89**	0.89	0.84	0.79**	0.79	0.52**	1.23***	1.20***	1.25***	1.01	0.65	7.02***	1.01	1.31	0.58
	(0.08)	(0.14)	(0.29)	(0.05)	(0.11)	(0.13)	(0.08)	(0.16)	(0.17)	(0.04)	(0.06)	(0.10)	(0.21)	(0.31)	(4.50)	(0.09)	(0.31)	(0.29)
DIS	1.30	1.01	0.00***	2.80***	2.78**	2.71	5.30***	5.01***	4.96**	1.39*	0.94	1.21	1.53	1.51	0.89	2.39***	1.63	0.00***
	(0.32)	(0.50)	(0.00)	(0.56)	(1.14)	(2.15)	(1.24)	(2.45)	(3.20)	(0.24)	(0.27)	(0.53)	(0.74)	(1.18)	(1.17)	(0.55)	(1.25)	(0.00)
AMV	1.12	1.82***	1.23	1.08	1.29**	1.08	1.05	1.35*	1.23	1.09	1.11	0.98	1.10	1.34**	0.71	0.95	1.33*	1.29
	(0.12)	(0.33)	(0.57)	(0.09)	(0.14)	(0.28)	(0.10)	(0.21)	(0.44)	(0.07)	(0.11)	(0.14)	(0.15)	(0.19)	(0.31)	(0.10)	(0.20)	(0.55)
Constant	0.02**	0.02	0.01	0.23	0.03	0.19	7.81	2.21	25.71	0.00***	0.00***	0.00***	0.04	6.56	0.00***	0.01**	0.00***	24.75
	(0.03)	(0.05)	(0.03)	(0.36)	(0.09)	(0.82)	(18.81)	(10.82)	(18.49)	(0.00)	(0.00)	(0.00)	(0.16)	(6.35)	(0.00)	(0.01)	(0.00)	(312.92)

Note. This table provides the regression results for each sector during the entire sample period (Model 1). It displays the relative risk ratios (RRR) and standard errors in parentheses of each variable in each *AVAR–GARCH* category. An RRR coefficient of less than 1 indicates that a firm was more likely to experience less-than-normal volatility, an RRR coefficient of 1 (or close to 1) shows that the independent variable had no effect on a firm's abnormal return volatility and an RRR coefficient greater than 1 denotes that a firm was more likely to experience abnormal return volatility. The abnormal return volatility (*AVAR–GARCH*) is classified into three categories: category 1 (low abnormal return volatility), category 2 (moderate abnormal return volatility) and category 3 (high abnormal return volatility). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Appendix 3.2: Robustness Test 2 – Alternate Proxy for Abnormal Return Volatility (*AVAR–GJR–GARCH*) (Continued)

Model 2: Economic Disruptions

	High-performing Sectors								
	Health Care			Information Technology			Energy		
	1	2	3	1	2	3	1	2	3
Variable	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR
*AVOL*DIS*	0.69***	0.71***	0.65***	0.83	1.11	1.01	0.82	0.95	3.71***
	(0.06)	(0.06)	(0.06)	(0.23)	(0.47)	(0.51)	(0.26)	(0.28)	(1.41)
*DISC*DIS*	0.00	0.00*	4.96*	0.98	0.92**	1.08	0.90	1.07	0.97
	(0.00)	(0.00)	(2.40)	(0.02)	(0.03)	(0.07)	(0.10)	(0.18)	(0.20)
*ILLIQ*DIS*	1.46	2.40**	7.41***	69.19**	66.16**	932.52**	1.03**	1.05***	1.00
	(0.78)	(1.05)	(3.22)	(118.06)	(120.34)	(277.32)	(0.01)	(0.02)	(0.03)
*BAS*DIS*	1.06	1.58	1.10	1.24	0.59	0.83	0.68	0.65*	1.63
	(0.17)	(0.57)	(0.55)	(0.28)	(0.24)	(0.37)	(0.22)	(0.15)	(0.82)
*MSA*DIS*	1.18*	1.21*	0.84	0.92	0.76***	0.83	0.88	1.13	0.91
	(0.10)	(0.14)	(0.13)	(0.08)	(0.07)	(0.27)	(0.14)	(0.27)	(0.26)
*CIT*DIS*	2.07	0.00***	1.43	1.39	0.22	26.81*	0.62	0.00***	0.00***
	(3.03)	(0.00)	(2.09)	(2.49)	(0.27)	(52.65)	(1.07)	(0.00)	(0.00)
*COE*DIS*	1.05	1.11	1.03	1.11***	0.31	0.00***	0.95	1.06	0.87
	(0.06)	(0.14)	(0.20)	(0.04)	(0.23)	(0.00)	(0.08)	(0.14)	(0.19)
*MBV*DIS*	0.74	0.33	0.69	0.91	0.37	0.63	0.00*	1.74	682.98
	(0.45)	(0.32)	(1.19)	(0.34)	(0.49)	(0.46)	(0.01)	(5.14)	(2.88)
*SIZE*DIS*	1.46*	1.43	0.01	0.69	0.58	0.81	1.21	0.81	1.27
	(0.33)	(0.51)	(0.05)	(0.29)	(0.47)	(0.64)	(0.34)	(0.33)	(0.67)
*AMV*DIS*	1.14	1.83*	0.16***	1.50	1.87	1.78	0.93	1.27	1.20
	(0.27)	(0.66)	(0.10)	(0.48)	(0.84)	(1.35)	(0.58)	(0.83)	(0.90)

Note. This table presents the regression results for each sector during economic disruptions (Model 2), which shows the interactions (in bold) of economic disruptions (*DIS*) with each independent variable as a separate regression, holding all other independent variables constant (a total of 10 independent regressions). The models were executed in this way to prevent the potential for multicollinearity of the *DIS* variable with other instances of *DIS* within the same regression. The results have been consolidated into one single table (above) with the standard errors in parentheses. It should be noted that the full factorial model has been estimated, which includes each independent variable separated being specified along with their interaction with *DIS*. For the purposes of brevity, only the RRR coefficients of interaction variables have been included to avoid extensively long results tables. The full results can be provided upon request. A relative risk ratio (RRR) less than 1 indicates that a firm was more likely to experience less-than-normal volatility, an RRR coefficient of 1 (or close to 1) indicates that the independent variable had no effect on a firm's abnormal return volatility and an RRR coefficient greater than 1 denotes that a firm was more likely to experience abnormal return volatility. Abnormal return volatility (*AVAR–GARCH*) is further classified into three categories, denoting its level: category 1 (low abnormal return volatility), category 2 (moderate abnormal return volatility) and category 3 (high abnormal return volatility). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Model 2: Economic Disruptions (Continued)

	Moderate-performing Sectors															Low-performing Sector		
	Consumer Discretionary			Financials			Industrials			Materials			Consumer Staples			Real Estate		
	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Variable	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR
*AVOL*DIS*	1.20*	1.21*	0 99	1.04	1.16	1.34	1.77**	1.32	3.38***	1.77**	1.32	3 38***	1 20	1.08	14.26**	0.85	0.96	0.62***
	(0.12)	(0.13)	(0.09)	(0.24)	(0.39)	(0.56)	(0.49)	(0.43)	(1.31)	(0.49)	(0.43)	(1.31)	(0.35)	(0.35)	(16.99)	(0.11)	(0.15)	(0.11)
*DISC*DIS*	0.02	207.29	0.02	33.41**	205.89**	3.40	0.82	45.04	79.22	0.82	45.04	79.22	0.00	0.30	0.09	414.73*	7.06	0.12
	(0.05)	(788.76)	(0.06)	(46.38)	(461.43)	(25.94)	(1.12)	(128.96)	(308.93)	(1.12)	(128.96)	(308.93)	(0.01)	(3.35)	(0.65)	(1.34)	(51.62)	(0.58)
*ILLIQ*DIS*	2.63***	7.83***	1.62*	4.51**	3.12	2.77	1.18	2.02*	1.49	1.18	2.02*	1.49	0 93	1.04	0 93	1.06	0.96	0.95
	(0.92)	(4.54)	(0.46)	(3.23)	(2.86)	(2.63)	(0.43)	(0.83)	(0.59)	(0.43)	(0.83)	(0.59)	(0.09)	(0.11)	(0.12)	(0.09)	(0.09)	(0.08)
*BAS*DIS*	0.98	1.00	0.70**	0.95	0.72*	0.74	0.89	0.81	0.74	0.89	0.81	0.74	1 13	1.67	1.81	1.35*	0.48	0.75
	(0.15)	(0.30)	(0.12)	(0.13)	(0.14)	(0.33)	(0.13)	(0.24)	(0.31)	(0.13)	(0.24)	(0.31)	(0.27)	(0.58)	(1.44)	(0.24)	(0.27)	(0.18)
*MSA*DIS*	0.92	1.20	1 11	1.04	1.02	1.15	1.00	0.84***	0.71**	1.00	0.84***	0.71**	0 97	0.86	1 35	0.99	1.35***	0.95
	(0.09)	(0.23)	(0.15)	(0.04)	(0.08)	(0.13)	(0.03)	(0.06)	(0.10)	(0.03)	(0.06)	(0.10)	(0.23)	(0.36)	(0.69)	(0.06)	(0.14)	(0.12)
*CIT*DIS*	0.00***	6.26	0 51	1.10	0.60	0.02***	0.97	0.44	0.00***	0.97	0.44	0.00***	7.09	4.08	73.50	0.00***	0.15	35.78***
	(0.00)	(9.65)	(0.66)	(0.73)	(0.88)	(0.02)	(0.82)	(0.68)	(0.00)	(0.82)	(0.68)	(0.00)	(13.71)	(8.54)	(368.99)	(0.00)	(0.25)	(5.55)
*COE*DIS*	1.06	0.84	1.06*	1.13**	1.18**	1.26***	0.97	1.00	0.87*	0.97	1.00	0.87*	1.01	0.97	0.88	1.09	0.71	0.97
	(0.05)	(0.13)	(0.04)	(0.06)	(0.08)	(0.11)	(0.02)	(0.05)	(0.07)	(0.02)	(0.05)	(0.07)	(0.05)	(0.06)	(0.12)	(0.08)	(0.18)	(0.13)
*MBV*DIS*	1.10	0.77	0.66	0.78	1.03	0.64	1.73***	1.25	0.39	1.73***	1.25	0 39	0.61	0.48	0.00***	0.43	0.16	13.35***
	(0.31)	(0.46)	(0.22)	(0.21)	(0.53)	(0.54)	(0.36)	(0.58)	(0.28)	(0.36)	(0.58)	(0.28)	(0.47)	(0.55)	(0.00)	(0.27)	(0.23)	(12.79)
*SIZE*DIS*	0.26**	0.53	0.80	1.25*	1.30	1.12	1.54*	0.73	0.60	1.54*	0.73	0.60	1 28	1.05	2 35	1.34	1.02	1.21
	(0.15)	(0.27)	(0.35)	(0.16)	(0.28)	(0.37)	(0.39)	(0.37)	(0.31)	(0.39)	(0.37)	(0.31)	(0.68)	(0.97)	(2.45)	(0.42)	(0.58)	(0.62)
*AMV*DIS*	0.78	0.64	0.77	1.11	0.64**	0.23***	0.76	0.67	1.32	0.76	0.67	1 32	0 52**	2.05	0.44	0.90	0.60*	0.70
	(0.17)	(0.22)	(0.38)	(0.21)	(0.14)	(0.10)	(0.15)	(0.21)	(0.79)	(0.15)	(0.21)	(0.79)	(0.16)	(0.93)	(0.49)	(0.18)	(0.17)	(0.34)

Note. This table presents the regression results for each sector during economic disruptions (Model 2), which shows the interactions (in bold) of economic disruptions (*DIS*) with each independent variable as a separate regression, holding all other independent variables constant (a total of 10 independent regressions). The models were executed in this way to prevent the potential for multicollinearity of the *DIS* variable with other instances of *DIS* within the same regression. The results have been consolidated into one single table (above) with the standard errors in parentheses. It should be noted that the full factorial model has been estimated, which includes each independent variable separated being specified along with their interaction with *DIS*. For the purposes of brevity, only the RRR coefficients of interaction variables have been included to avoid extensively long results tables. The full results can be provided upon request. A relative risk ratio (RRR) less than 1 indicates that a firm was more likely to experience less-than-normal volatility, an RRR coefficient of 1 (or close to 1) indicates that the independent variable had no effect on a firm's abnormal return volatility and an RRR coefficient greater than 1 denotes that a firm was more likely to experience abnormal return volatility. Abnormal return volatility (*AVAR–GARCH*) is further classified into three categories, denoting its level: category 1 (low abnormal return volatility), category 2 (moderate abnormal return volatility) and category 3 (high abnormal return volatility). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Appendix 3.3: Robustness Test 3 – Alternate Proxies for Independent Variables

Model 1: Entire Sample Period

	High-performing Sectors								
	Health Care			Information Technology			Energy		
	1	2	3	1	2	3	1	2	3
Variable	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR
ATR	1.28***	1.38***	1.39***	1.23***	1.35***	1.43***	1.21***	1.24***	1.32***
	(0.09)	(0.12)	(0.13)	(0.05)	(0.08)	(0.13)	(0.06)	(0.06)	(0.07)
DISC	0.99	0.94	1.02*	1.01	1.03*	1.05	1.00	1.00	1.00
	(0.01)	(0.09)	(0.01)	(0.01)	(0.02)	(0.04)	(0.00)	(0.01)	(0.01)
LIQ	0.70***	0.59***	0.48***	0.62***	0.50***	0.25***	0.45***	0.39***	0.43***
	(0.04)	(0.05)	(0.06)	(0.06)	(0.08)	(0.10)	(0.05)	(0.06)	(0.10)
BAS	1.18**	1.12	0.73	0.95	0.92	1.36	0.80*	0.94	0.51***
	(0.08)	(0.12)	(0.14)	(0.12)	(0.16)	(0.51)	(0.10)	(0.14)	(0.13)
MSA	1.05**	0.98	1.05	1.06	1.02	0.61	1.00	1.04	0.88**
	(0.02)	(0.03)	(0.04)	(0.04)	(0.05)	(0.23)	(0.01)	(0.03)	(0.05)
CIT	1.70	6.16**	0.00***	1.04	0.00***	0.00***	0.82	0.00***	0.00***
	(1.02)	(4.45)	(0.00)	(0.66)	(0.00)	(0.00)	(1.53)	(0.00)	(0.00)
COE	0.99	1.00	0.98	0.96*	0.97	0.90	1.04***	1.01	1.13**
	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.06)	(0.02)	(0.02)	(0.06)
MBV	0.98	1.34	1.08	1.78***	1.89***	5.26***	1.73**	2.14*	0.80
	(0.15)	(0.29)	(0.36)	(0.23)	(0.40)	(3.15)	(0.41)	(0.84)	(0.73)
SIZE	1.03	0.88	0.95	1.08	1.14	0.64	0.94	0.69***	1.81*
	(0.08)	(0.11)	(0.19)	(0.11)	(0.17)	(0.24)	(0.08)	(0.09)	(0.61)
DIS	1.86*	1.52	6.21	1.44	0.69	1.43	2.77**	3.89**	3.01
	(0.61)	(1.01)	(7.32)	(0.75)	(0.52)	(2.08)	(1.37)	(2.33)	(2.65)
AMV	1.08	1.51**	0.85	1.11	0.99	1.25	0.95	1.41	0.96
	(0.12)	(0.25)	(0.29)	(0.15)	(0.19)	(0.26)	(0.18)	(0.37)	(0.41)
Constant	6.62*	27.87**	0.34	0.19	0.13	1.56	0.09	3.16	0.00***
	(7.01)	(45.48)	(0.81)	(0.30)	(0.28)	(1.24)	(0.14)	(7.14)	(0.00)

Note. This table provides the regression results for each sector during the entire sample period (Model 1). It displays the relative risk ratios (RRR) and standard errors in parentheses of each variable in each *AVAR–GARCH* category. An RRR coefficient of less than 1 indicates that a firm was more likely to experience less-than-normal volatility, an RRR coefficient of 1 (or close to 1) shows that the independent variable had no effect on a firm's abnormal return volatility and an RRR coefficient greater than 1 denotes that a firm was more likely to experience abnormal return volatility. The abnormal return volatility (*AVAR–GARCH*) is classified into three categories: category 1 (low abnormal return volatility), category 2 (moderate abnormal return volatility) and category 3 (high abnormal return volatility). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Model 1: Entire Sample Period (Continued)

	Moderate-performing Sectors															**Low-performing Sector**		
	Consumer Discretionary			**Financials**			**Industrials**			**Materials**			**Consumer Staples**			**Real Estate**		
	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Variable	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR
ATR	1.14***	1.23***	1.26***	1.20***	1.25***	1.27***	1.19***	1.24***	1.30***	1.16***	1.25***	1 28***	1.17***	1.23***	1.54***	1.23***	1.33***	1.36***
	(0.03)	(0.05)	(0.07)	(0.06)	(0.08)	(0.09)	(0.05)	(0.08)	(0.12)	(0.02)	(0.03)	(0.04)	(0.05)	(0.09)	(0.15)	(0.05)	(0.07)	(0.09)
DISC	1.01**	0.98**	1.01	1.27	1.47	0.11	1.00	0.30*	0.48*	1.01**	1.00	1.02***	0.87*	0.99	1.76**	1.00	0.99	0.97
	(0.00)	(0.01)	(0.01)	(0.30)	(0.54)	(0.17)	(0.01)	(0.21)	(0.21)	(0.00)	(0.01)	(0.01)	(0.07)	(0.18)	(0.48)	(0.00)	(0.01)	(0.07)
LIQ	0.50***	0.32***	0.38***	0.46***	0.38***	0.38***	0.48***	0.37***	0.31***	0.58***	0.46***	0.47***	0.30***	0.26***	0.12***	0.50***	0.44***	0.39***
	(0.03)	(0.04)	(0.07)	(0.04)	(0.05)	(0.07)	(0.04)	(0.05)	(0.07)	(0.02)	(0.03)	(0.04)	(0.06)	(0.09)	(0.06)	(0.03)	(0.04)	(0.05)
BAS	0.95	1.23*	1.51**	1.07	1.47***	1.12	0.91	0.96	1.26	0.91***	0.98	0 91	0.95	1.18	1.05	1.16*	1.20	1.73**
	(0.06)	(0.15)	(0.26)	(0.07)	(0.15)	(0.23)	(0.06)	(0.12)	(0.23)	(0.03)	(0.06)	(0.09)	(0.12)	(0.34)	(0.63)	(0.09)	(0.17)	(0.47)
MSA	0.99	0.96	0.91	1.00	0.95	1.03	1.02*	0.99	1.01	1.01	1.02*	1.01	1.00	0.69**	0.40*	1.01	0.98	1.18**
	(0.02)	(0.05)	(0.10)	(0.02)	(0.04)	(0.05)	(0.01)	(0.03)	(0.07)	(0.01)	(0.01)	(0.01)	(0.07)	(0.13)	(0.21)	(0.02)	(0.06)	(0.08)
CIT	1.26	4.53***	3.14	2.23**	1.46	0.00***	1.35	1.44	1.53	1.97***	1.33	2 13	2.85	0.00***	0.00***	1.09	3.90*	0.00***
	(0.58)	(2.57)	(2.82)	(0.77)	(1.20)	(0.00)	(0.58)	(1.23)	(1.48)	(0.51)	(0.68)	(1.26)	(1.91)	(0.00)	(0.00)	(0.54)	(2.93)	(0.00)
COE	1.00	0.99	1.00	1.03*	1.08**	1.02	0.97***	0.97	0.94**	0.97***	0.96***	1.00	1.02	1.03	0.86	0.99	1.10*	1.00
	(0.00)	(0.01)	(0.01)	(0.02)	(0.03)	(0.04)	(0.01)	(0.02)	(0.03)	(0.00)	(0.01)	(0.01)	(0.02)	(0.03)	(0.10)	(0.03)	(0.06)	(0.09)
MBV	1.69***	2.04***	1.77**	1.98***	3.10***	2.18*	1.54***	1.68***	1.44	1.32***	1.40***	1.60***	3.90***	1.30	12.56***	0.72	1.16	0.21***
	(0.17)	(0.49)	(0.49)	(0.35)	(1.04)	(1.03)	(0.15)	(0.31)	(0.34)	(0.08)	(0.14)	(0.24)	(1.91)	(1.21)	(29.70)	(0.14)	(0.38)	(0.12)
SIZE	1.09	1.04	1.08	0.89**	0.91	0.80	0.79**	0.77	0.52**	1.23***	1.21***	1 25***	1.06	0.65	7.07***	1.00	1.34	0.58
	(0.08)	(0.14)	(0.29)	(0.05)	(0.11)	(0.12)	(0.08)	(0.16)	(0.17)	(0.04)	(0.06)	(0.10)	(0.22)	(0.31)	(4.53)	(0.09)	(0.33)	(0.29)
DIS	1.25	1.25	0.00***	2.92***	3.23***	3.16	5.58***	4.49***	5.17***	1.28	0.83	1 15	1.23	1.29	0.86	2.31***	1.51	0.00***
	(0.31)	(0.64)	(0.00)	(0.61)	(1.38)	(2.60)	(1.34)	(2.04)	(3.22)	(0.20)	(0.23)	(0.49)	(0.58)	(0.97)	(1.33)	(0.61)	(1.32)	(0.00)
AMV	1.05	1.76***	1.03	0.93	1.08	0.91	0.97	1.25	1.10	1.04	1.03	0 90	0.92	1.07	0.46	0.91	1.19	1.17
	(0.11)	(0.34)	(0.58)	(0.08)	(0.12)	(0.24)	(0.10)	(0.18)	(0.39)	(0.07)	(0.11)	(0.13)	(0.13)	(0.20)	(0.25)	(0.11)	(0.24)	(0.45)
Constant	0.11**	2.02	2.03	5.74	1.76	7.04	320.95***	31.92	302.41**	0.51	1.28	0 18	0.01	0.38	0.00***	1.22	0.00	168.77
	(0.11)	(4.50)	(8.27)	(6.67)	(3.80)	(18.05)	(524.65)	(105.39)	(150.66)	(0.25)	(1.01)	(0.25)	(0.04)	(2.42)	(0.00)	(2.24)	(0.01)	(143 92)

Note. This table provides the regression results for each sector during the entire sample period (Model 1). It displays the relative risk ratios (RRR) and standard errors in parentheses of each variable in each *AVAR–GARCH* category. An RRR coefficient of less than 1 indicates that a firm was more likely to experience less-than-normal volatility, an RRR coefficient of 1 (or close to 1) shows that the independent variable had no effect on a firm's abnormal return volatility and an RRR coefficient greater than 1 denotes that a firm was more likely to experience abnormal return volatility. The abnormal return volatility (*AVAR–GARCH*) is classified into 3 categories, which include category 1 (low abnormal return volatility), 2 (moderate abnormal return volatility) and 3 (high abnormal return volatility). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Appendix 3.3: Robustness Test 3 – Alternate Proxies for Independent Variables (Continued)

Model 2: Economic Disruptions

	High-performing Sectors								
	Health Care			Information Technology			Energy		
	1	2	3	1	2	3	1	2	3
Variable	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR
*ATR*DIS*	0.74***	0.70***	0.68***	0.79***	0.80***	0.82	0.78***	0.83**	0.96
	(0.05)	(0.05)	(0.05)	(0.05)	(0.07)	(0.10)	(0.06)	(0.07)	(0.10)
*DISC*DIS*	0.00**	0.00**	57.23	0.98	0.93	1.10*	1.07	1.31	1.39
	(0.00)	(0.00)	(246.26)	(0.02)	(0.05)	(0.06)	(0.18)	(0.30)	(0.40)
*LIQ*DIS*	1.34*	0.66	0.16***	0.44***	0.30***	0.27**	0.84	0.68	0.78
	(0.21)	(0.22)	(0.10)	(0.14)	(0.14)	(0.15)	(0.14)	(0.16)	(0.18)
*BAS*DIS*	1.11	1.76	1.17	1.42	0.50	1.34	0.36***	0.34***	0.49
	(0.17)	(0.72)	(0.52)	(0.50)	(0.30)	(1.15)	(0.14)	(0.11)	(0.28)
*MSA*DIS*	1.16	1.16	0.76	0.98	0.89	0.93	1.10	1.43	1.41
	(0.12)	(0.16)	(0.18)	(0.09)	(0.09)	(0.39)	(0.25)	(0.46)	(0.52)
*CIT*DIS*	2.77	0.00***	1.43	1.04	0.09*	62.12*	0.82	0.00***	0.00***
	(4.23)	(0.00)	(2.11)	(1.81)	(0.13)	(136.40)	(1.53)	(0.00)	(0.00)
*COE*DIS*	1.02	1.08	1.00	1.11**	0.61	0.00***	1.13	1.26	1.18
	(0.06)	(0.14)	(0.19)	(0.04)	(0.20)	(0.00)	(0.14)	(0.21)	(0.27)
*MBV*DIS*	1.37	0.68	1.31	2.22*	1.71	1.94	0.00	5.66	7.29**
	(1.05)	(0.84)	(3.02)	(1.05)	(1.85)	(2.58)	(0.00)	(19.83)	(4.05)
*SIZE*DIS*	1.48*	1.43	0.01	0.69	0.58	0.81	1.21	0.80	1.37
	(0.33)	(0.51)	(0.05)	(0.29)	(0.47)	(0.64)	(0.34)	(0.33)	(0.67)
*AMV*DIS*	1.36	4.76**	0.63	1.17	0.90	1.12	0.55	0.80	0.75
	(0.40)	(3.50)	(0.72)	(0.36)	(0.45)	(0.60)	(0.41)	(0.61)	(0.82)

Note. This table presents the regression results for each sector during economic disruptions (Model 2), which shows the interactions (in bold) of economic disruptions (*DIS*) with each independent variable as a separate regression, holding all other independent variables constant (a total of 10 independent regressions). The models were executed in this way to prevent the potential for multicollinearity of the *DIS* variable with other instances of *DIS* within the same regression. The results have been consolidated into one single table (above) with the standard errors in parentheses. It should be noted that the full factorial model has been estimated, which includes each independent variable separated being specified along with their interaction with *DIS*. For the purposes of brevity, only the RRR coefficients of interaction variables have been included to avoid extensively long results tables. The full results can be provided upon request. A relative risk ratio (RRR) less than 1 indicates that a firm was more likely to experience less-than-normal volatility, an RRR coefficient of 1 (or close to 1) indicates that the independent variable had no effect on a firm's abnormal return volatility and an RRR coefficient greater than 1 denotes that a firm was more likely to experience abnormal return volatility. Abnormal return volatility (*AVAR–GARCH*) is further classified into three categories, denoting its level: category 1 (low abnormal return volatility), category 2 (moderate abnormal return volatility) and category 3 (high abnormal return volatility). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Model 2: Economic Disruptions (Continued)

	Moderate-performing Sectors															**Low-performing Sector**		
	Consumer Discretionary			**Financials**			**Industrials**			**Materials**			**Consumer Staples**			**Real Estate**		
	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Variable	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR	RRR
*ATR*DIS*	1.01	0.99	0.85***	0.95	0 94	0.96	1.06	1.00	1.14	0.94	0.91	0.91	1.04	0.98	1.08	0.89*	0.92	0.67***
	(0.07)	(0.08)	(0.05)	(0.09)	(0.12)	(0.14)	(0.09)	(0.11)	(0.15)	(0.08)	(0.12)	(0.13)	(0.08)	(0.12)	(0.10)	(0.06)	(0.09)	(0.08)
*DISC*DIS*	0.04	721.27	0.55	60.60	258.36**	15.02	0.56	67.88	14.44	1.80*	1.39	4.51***	0.00	1.37	0.00	223.46	0.41	0.13
	(0.13)	(3,126.79)	(1.17)	(89.02)	(594.64)	(98.96)	(0.75)	(202.72)	(41.96)	(0.58)	(0.63)	(2.59)	(0.03)	(16.60)	(0.03)	(797.65)	(3.29)	(0.84)
*LIQ*DIS*	0.74*	0.45**	1.03	0.96	0 92	0.73	0.80	0.38***	0.58	1.04	1.00	1.06	0.91	0.68	0.38**	0.76	0.71	0.96
	(0.14)	(0.18)	(0.55)	(0.13)	(0.16)	(0.18)	(0.14)	(0.11)	(0.21)	(0.04)	(0.07)	(0.11)	(0.20)	(0.25)	(0.15)	(0.16)	(0.17)	(0.29)
*BAS*DIS*	1.08	1.21	0.89	1.00	0.74	0.69	0.88	0.80	0.74	0.90	0.71**	0.77	1.45	2.28*	1.19	1.19	0.39**	0.82
	(0.18)	(0.48)	(0.24)	(0.15)	(0.16)	(0.33)	(0.13)	(0.24)	(0.30)	(0.08)	(0.11)	(0.14)	(0.41)	(1.01)	(1.44)	(0.22)	(0.17)	(0.27)
*MSA*DIS*	0.83*	0.91	1.00	0.99	0 99	1.11	1.00	0.86**	0.72**	1.02	0.98	0.89	1.01	0.64	0.30**	0.96	1.39**	0.99
	(0.09)	(0.23)	(0.19)	(0.04)	(0.08)	(0.14)	(0.03)	(0.06)	(0.10)	(0.04)	(0.07)	(0.07)	(0.28)	(0.33)	(0.16)	(0.07)	(0.19)	(0.13)
*CIT*DIS*	0.00***	7.31	0.04***	0.68	0 38	355.36***	0.77	0.27	0.00***	0.96	0.00***	3.39	5.19	2.86	0.26	0.00***	0.03**	1.92***
	(0.00)	(10.32)	(0.05)	(0.46)	(0.59)	(574.76)	(0.64)	(0.45)	(0.00)	(0.62)	(0.00)	(4.22)	(9.87)	(5.77)	(0.64)	(0.00)	(0.04)	(0.33)
*COE*DIS*	1.05	0.85	1.00	1.08	1 13*	1.22**	0.99	1.03	0.90	0.98*	0.94***	0.93***	0.96	0.93	0.58*	1.13	0.75	1.06
	(0.05)	(0.09)	(0.07)	(0.06)	(0.07)	(0.12)	(0.02)	(0.05)	(0.08)	(0.01)	(0.02)	(0.02)	(0.04)	(0.06)	(0.17)	(0.10)	(0.18)	(0.16)
*MBV*DIS*	1.66	1.96	0.87	0.96	1 16	0.97	1.37	0.97	0.25*	1.46***	1.18	2.97***	1.80	0.93	0.00***	0.69	0.27	1.61
	(0.53)	(1.35)	(0.47)	(0.27)	(0.55)	(0.83)	(0.28)	(0.48)	(0.19)	(0.21)	(0.32)	(1.07)	(1.73)	(1.41)	(0.00)	(0.46)	(0.44)	(2.76)
*SIZE*DIS*	0.38*	0.54	0.82	0.38*	0 54	0.82	1.57*	0.62	0.60	1.07	1.00	1.12	1.51	1.09	2.44	1.34	0.97	1.19
	(0.15)	(0.27)	(0.35)	(0.16)	(0.28)	(0.37)	(0.39)	(0.37)	(0.31)	(0.39)	(0.37)	(0.31)	(0.68)	(0.97)	(2.45)	(0.42)	(0.58)	(0.62)
*AMV*DIS*	0.83	0.59	1.05	1.12	0.66**	0.24***	0.84	0.72	1.30	0.90	0.85	0.62	0.56*	3.01*	1.12	0.82	0.58	0.53
	(0.19)	(0.20)	(0.62)	(0.21)	(0.14)	(0.10)	(0.16)	(0.23)	(0.86)	(0.12)	(0.19)	(0.21)	(0.17)	(2.00)	(1.82)	(0.19)	(0.23)	(0.34)

Note. This table presents the regression results for each sector during economic disruptions (Model 2), which shows the interactions (in bold) of economic disruptions (*DIS*) with each independent variable as a separate regression, holding all other independent variables constant (a total of 10 independent regressions). The models were executed in this way to prevent the potential for multicollinearity of the *DIS* variable with other instances of *DIS* within the same regression. The results have been consolidated into one single table (above) with the standard errors in parentheses. It should be noted that the full factorial model has been estimated which includes each independent variable separated being specified along with their interaction with *DIS*. For the purposes of brevity, only the RRR coefficients of interaction variables have been included to avoid extensively long results tables. The full results can be provided upon request. A relative risk ratio (RRR) less than 1 indicates that a firm was more likely to experience less-than-normal volatility, an RRR coefficient of 1 (or close to 1) indicates that the independent variable had no effect on a firm's abnormal return volatility and an RRR coefficient greater than 1 denotes that a firm was more likely to experience abnormal return volatility. Abnormal return volatility (*AVAR–GARCH*) is further classified into three categories, denoting its level: category 1 (low abnormal return volatility), category 2 (moderate abnormal return volatility) and category 3 (high abnormal return volatility). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Appendix 4: Benefits and Drawbacks of Each SEO Type

SEO Type	Benefits Obtained	Drawbacks to Consider
Non-renounceable rights issue	1. Allows institutional and retail investors an equal opportunity to participate in the SEO. 2. Consists of high disclosure requirements, which provides investors with greater information transparency, thus increasing the chance for shareholder participation. 3. No limit on capital that can be raised.	1. Rights cannot be sold by a shareholder to a third party. If the shareholder does not participate in the SEO, they feel the full effects of share dilution. 2. Higher cost owing to the larger disclosure requirements. 3. Longer processing times (up to 23 business days). 4. Offered on a pro-rata basis, which is upon the discretion of the issuing firm. The pro-rata ratio can sometimes be small.
Placement & renounceable rights issue	1. Dedicated institutional component to expedite the capital-raising process. 2. Consideration of retail investor with a dedicated rights issue, with the benefit of renounceability offered. 3. High disclosure requirements in the rights issue component to provide transparency to shareholders.	4. Higher cost because two types of SEOs issued (i.e. placement for institutional investors and rights issue for retail investors). 5. Higher cost owing to the larger disclosure requirements for the retail component (i.e. rights issue). 6. Longer processing times (up to 23 business days) because of the retail component. 7. Rights issue component offered on a pro-rata basis, which is upon the discretion of the issuing firm. The pro-rata ratio can sometimes be small.
Renounceable rights issue	1. Allows institutional and retail investors an equal opportunity to participate in the SEO. 2. Consists of high disclosure requirements, which provides investors with greater information transparency, thus increasing the chance for shareholder participation. 3. No limit on capital that can be raised. 4. Rights can be sold by a shareholder to a third party if the shareholder does not wish to partake in the SEO. This helps to offset the share dilution impact.	1. Higher cost owing to the larger disclosure requirements. 2. Longer processing times (up to 23 business days). 3. Offered on a pro-rata basis, which is upon the discretion of the issuing firm. The pro-rata ratio can sometimes be small.

Placement & SPP	1. Dedicated institutional component to expedite the capital-raising process. 2. Consideration of retail investor via a dedicated rights issue, with the benefit of renounceability offered. 3. High disclosure requirements in the rights issue component to provide transparency to shareholders. 4. SPP component allows a larger number of shares to be purchased by shareholders since it is not restricted by a pro-rata offer. 5. SPP component has lower transaction costs owing to no underwriting fees and minimal disclosure documentation (i.e. brief SPP booklet).	1. Shareholders who do not participate will experience share dilution. 2. Longer timetable between execution and settlement date since SPPs can be kept open for up to 6 weeks.
Private placement	1. Quickest turnaround time (3–4 days). Beneficial for firms that need capital immediately. 2. High chance of success for the capital is being raised from highly credible institutional investors. 3. Lowest issuance cost owing to the limited disclosure requirements.	1. Firms are limited to issuing up to 15% of the existing number of shares outstanding. 2. Retail shareholders are excluded completely. 3. Not ideal during economic disruptions; retail investors do not obtain the opportunity to buffer the effects of share dilution (especially during such volatile times).
Placement & non-renounceable rights issue	1. Dedicated institutional component to expedite the capital-raising process. 2. Consideration of retail investor with a dedicated rights issue, with the benefit of renounceability offered. 3. High disclosure requirements in the rights issue component to provide transparency to shareholders.	1. Higher cost owing to two types of SEOs being issued (i.e. placement for institutional investors and rights issue for retail investors). 2. Higher cost owing to the larger disclosure requirements for the retail component (i.e. rights issue). 3. Longer processing times (up to 23 business days) because of the retail component. 4. Rights issue component offered on a pro-rata basis, which is upon the discretion of the issuing firm. The pro-rata ratio can sometimes be small.

Note. This table provides a summary of the benefits and drawbacks firms can expect when choosing each SEO type.