Topics in market microstructure, misconduct and systemic risk: An empirical analysis of the South African equity market

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Abstract

Three distinct but interrelated studies with their foundations in recent developments in the South African capital markets are presented in this thesis. The first study presents an empirical analysis of the systemic risk exposures and contributions of 125 financial institutions between 2003 and 2018. Using two popular measures of systemic risk, the marginal expected shortfall (MES) and conditional capital shortfall (SRISK), it is shown that banking institutions are collectively the largest contributors to systemic risk in the financial system. Surprisingly, further analysis reveals that despite the high levels of market concentration and interconnectedness, SRISK increases are not propagated across sectors. Notwithstanding the foregoing, the results provide support for previous empirical findings of the systemic importance of banking institutions. In addition, causality analysis of the relationship between SRISK in the banking sector and the prime lending rate provides new evidence that complements previous theories of systemic risk spillovers into the real economy, specifically through lending activity. Overall, the results illustrate the potential for the use of market based measures in supporting macroprudential oversight and informing policy decisions.

The second essay addresses questions related to misconduct contagion and crowding. Crowding is a form of clustering in which the behaviour of market participants leads to congestion on one side of the market, otherwise known as crowded trades. We propose a measure of crowding, based on intraday trade data and use the measure to study changes in the trading environment following allegations of misconduct. Evidence of coincidental and significant changes in crowding and trade volumes is reported in the first set of empirical results, consistent with the notion of information contagion and how firm-specific developments may have significance for other firms. More importantly, the study demonstrates empirically, that crowding increases exposure to adverse spillover effects and deteriorates liquidity in the equity market. We further contributes to the literature, by documenting novel evidence of the asymmetric effects of intraday volatility and trade volume on MES and quoted spreads, respectively, that is dependent on the crowd direction. Relative to buy-crowds, sell-crowds amplify the effect volatility has on MES and reduce the effect trade volume has on quoted spreads.

In the third study, the aim is to investigate the implications of domestic cross-listings for the market quality of twenty-six firms that cross-listed between April 2018 and April 2020, following a series of amendments to legislation. Evidence of

significant improvements in market quality in the six months after a cross limited, even after adjusting for market quality changes of firms that do not cross-list. Additionally, our results offer no support for the hypothesis that there is a significant difference in market quality changes observed for high and low liquidity firms, in contrast to previous cross-listing studies. Lastly, by consolidating order books across exchanges, it is shown that the price dimension of execution quality can be improved across all venues, even after controlling for liquidity characteristics. We conclude that interoperability between venues can be effective in reducing the cost of trading, and is therefore necessary for a domestic cross-listing to be worthwhile. Collectively, the findings contribute to the ongoing debate around best execution standards and inter-market competition in South Africa's equity market.

Statement of Originality

This thesis is being submitted to Macquarie University and the University of Cape Town in accordance with the Cotutelle agreement dated 10 May 2017.

I declare that to the best of my knowledge and belief, this thesis is based on my original work and contains no material previously published or written by another person except where acknowledgements are made in the thesis itself.

Signed

Date

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Chapter 1

Introduction

Three distinct, but interrelated studies with their foundations in recent developments in the South African capital markets, are presented in this thesis. In particular, this thesis is concerned with systemic risk and market microstructure, from the perspective of market design and information contagion. Among other reasons, the studies are motivated by the bias towards evidence from developed markets, in each of the identified research areas, despite the general improvement in the quality of available emerging market data. The objective, therefore, is to provide a more relevant point of reference for regulators and market participants in emerging markets, while still addressing as yet unanswered questions in the literature. In the sections that follow, each study is introduced with a brief synopsis of the research design and the contributions to the literature.

1.1 A Systemic Risk Analysis of South African Financial Institutions

A significant contributing factor to the severity of the global financial crisis in 2008, was the contagion channel created by interconnections in the financial system. Highly interconnected, and concentrated market structures in South Africa's financial sector can only lead one to question whether financial stability hangs in the balance, seeing that a single shock may very well be amplified into a systemic event. The unprecedented simultaneous failure of ten money market funds in 2014, following the failure of a single bank, may be recognized by many as a premonitory sign of the financial system's fragility. Evidently, under prevailing market structures, it would only prudent to have in place measures and tools to support supervisory functions in the timely assessment of the financial system's soundness. A case for the use of market-based measures of systemic risk in South Africa's financial sector is presented in this study.

Using marginal expected shortfall (MES) and conditional capital shortfall (SRISK), an assessment of the dynamics of systemic risk is carried out for a sample of 125 Johannesburg Stock Exchange listed financial institutions. The measures are estimated daily, starting in January 2003 through to the end of 2018. Contributions by industry groups to system-wide distress are examined, and additional tests are carried out to assess the robustness and sensitivity of the estimated measures. Consideration is also given to the view that systemic risk has adverse effects on the real economy by interrogating the relationship between systemic risk and lending activity.

It is shown that the banking and insurance sectors are the largest contributors to domestic systemic risk in South Africa, consistent with the persistently high levels of market concentration and interconnectedness. Further analysis shows that rankings of systemic importance implied by MES and SRISK are consistent with conventional indicators widely used in regulatory practice. The results also provide new evidence of structural breaks in both SRISK and MES following shocks to the financial system. In addition, causality analysis of the relationship between SRISK in the banking sector and the prime lending rate, reveals new evidence that complements previous findings of systemic risk spilling over into the real economy through lending activity.

To date, there has been limited research on systemic risk in South Africa's financial system. Collectively, the results reported here provide new insight into the dynamics of systemic risk spillovers between sectors, while also offering support for previous theories of the systemic importance of banking institutions. The findings are equally relevant to the current debate on how concentration and interconnectedness pose a threat to the stability in the financial sector and the real economy.

1.2 Misconduct Contagion and Crowding in the Stock Market: Evidence from South Africa

Several studies have shown that more commonality in investments increases price dislocation and pay-off correlations, both of which are significant considerations in the measurement of systemic risk. Crowding has been identified as one such form of clustering, where the behaviour of market participants leads to congestion on one side of the market, otherwise known as crowded trades. Diverging from prior research, this study examines the phenomenon of crowding in the context of corporate misconduct and malfeasance.

Using daily data for a sample of Johannesburg Stock Exchange listed equities, the study provides new evidence of significant changes in crowding following allegations of misconduct. The first set of tests examines how information flows between securities in the equity market. For each firm, an information network of follower firms is identified using return predictability implied by Granger causality regressions. Then, using generally accepted proxies for investor attention —including, news coverage, analyst coverage, institutional ownership, momentum and various fundamental ratios —an assessment of the role played by the proxies in determining return predictability is carried out. The reported evidence suggests that greater firm specific investor attention shortens delays in the diffusion of information into followers' prices. The conjecture that changes in a firm's trading environment following allegations of misconduct may be fully, or partially mirrored in the firm's information network arises from this finding, and is examined further using event study methodologies.

The study considers eight instances of misconduct that occurred between December 2015 and May 2019. In cases of corporate misconduct, an assessment of changes in crowding and the trading environment is made, for the implicated firm and its information network. A new measure of crowding is proposed, defined as the absolute value of the imbalance between buyer and seller initiated trade volumes, divided by the number of outstanding shares. It is shown that crowding increases significantly for implicated firms in the post event period. In contrast, for the information networks, crowding is observed to decline significantly. Where malfeasance occurs, changes are estimated for a group of firms with limited exposure to the domestic economic climate. Here, there is limited evidence of significant increases in crowding, however, quoted spreads and intraday volatility are observed to increase significantly.

An examination of the interrelationship between crowding, systemic risk and liquidity reveals that the proposed measure of crowding has significant forecasting power for both MES and quoted spreads. Furthermore, novel evidence suggests that intraday volatility and volume traded have asymmetric effects on MES and quoted spreads respectively, conditional on the direction of the imbalance between buyer and seller initiated trades. Overall, the evidence presented in this study is consistent with the views that crowding increases exposure to systemic risk and deteriorates liquidity.

In brief, the study contributes to a growing body of literature that sheds light on how investor behaviour influences market quality and stability. To the best of our knowledge, this is the first attempt at a cross-disciplinary investigation of crowding. Where crowding has previously been addressed in the literature, limited attention has been given to how this phenomenon is affected by exogenous events. Furthermore, the examination of changes in the trading and liquidity environments of linked firms builds on the literature that examines information contagion in the public equity markets. Lastly, evidence of the interrelationship between crowding, systemic risk and liquidity, demonstrates how market clusters may increase exposure to systemic risk and deteriorate market quality, in line with existing theories.

1.3 Cross-listing in Emerging Markets and Market Quality: Evidence from the Johannesburg Stock Exchange

While it is common for firms to cross-list and maintain listings in multiple jurisdictions, doing so domestically is rare. Consequently, there is limited evidence of the implications that domestic cross-listings have for market quality. Notwithstanding the foregoing, available evidence suggests that the benefits often associated with cross-listings are conditional on the destination market being, inter alia —larger, more developed, and more liquid —and having stricter disclosure standards. In a domestic setting, several of the hypotheses on the sources of the value created by cross-listing become inconsequential. The question still stands, whether there is a benefit to cross-listing in the absence of the information and microstructure asymmetries associated with an additional listing on a non-domestic exchange. This study contributes to the cross-listing literature with an empirical examination of the South African equity market, given recent regulatory developments that paved the way for domestic cross-listings.

Using intraday data and a matched sample design, the study presents an investigation of market quality changes for a sample of twenty-six Johannesburg Stock

Exchange listed firms, that cross-listed on A2X Markets between April 2018 and April 2020. Market quality metrics considered in the assessment include: quoted and effective spreads, volume traded, intraday volatility and quote to trade ratios. The results provide weak evidence of a significant decline in transaction costs and a decline in trade activity over the six months after a cross-listing. Consideration is also given to the possibility of the impact varying with a firm's pre-cross listing liquidity characteristics. It is demonstrated that market quality changes do not differ significantly across liquidity groups. Furthermore, strong evidence is presented in support of the view that in a multi-market setting created by domestic cross-listings, the home market will be the dominant market.

The evidence also shows that a consolidated order book constructed using basic best execution standards, would significantly reduce transaction costs and improve liquidity across trading venues. This finding suggests that interoperability between venues is a requisite for an improvement in market quality following a domestic cross-listing.

An inherent contribution of the study lies in the explicit examination of domestic cross listings, as past authors have almost exclusively studied international cross-listings. The analysis also advances the discourse concerned with whether a cross-listing is, in and of itself a value enhancing decision, in the absence of market frictions and information asymmetries associated with the benefits of international cross-listings. Most important, is the unambiguous evidence of the effectiveness of interoperability between venues in reducing the cost of trading. An immediate application of these results is to the ongoing policy debate around inter-market competition and best execution in the new multi-market environment for South African securities.

1.4 Scope and Organization of the Studies

To summarize, this thesis aims to contribute to ongoing debates around stability, market quality, and market design in the South African equity market. In particular, the main research questions relate to the measurement of systemic risk, the interrelationship between misconduct contagion, crowding and systemic risk, and the multi-market environment created by domestic cross-listings. The first study presented in Chapter 3 reveals how systemic risk contributions of the financial sector may spill over into the real economy through lending activity. Chapter 4 demonstrates how synchronicity in the trading behaviour of market participants increases exposure to systemic risk and deteriorates liquidity. The last study in Chapter 5, has its foundations in the cross-listing literature and investigates whether interoperability between trading venues plays a role in the quality of the trading environment following a domestic cross-listing. Chapter 6 presents the overall conclusions and highlights areas with scope for future research.

Chapter 2

Institutional Background

2.1 South African Equity Market

South Africa's primary listing venue is the Johannesburg Stock Exchange (JSE). According to a dataset provided by the exchange, at the end of March 2021, there were 323 listed securities in the equity market, with a total market capitalisation of approximately \$1.1 trillion. Salient characteristics of the equity market that have persisted over time, include high levels of concentration, in both value and liquidity. For example, approximately 80% of daily value traded can be attributed to the forty largest equities, which collectively account for 89% of market capitalisation. Furthermore, only five stocks make up 49% of the JSE's total equity market value. Due to the liquidity challenges generally faced by smaller equities, 148 companies have de-listed since 2015, further contributing to the high levels of concentration in the equity market. In addition to the JSE, there are four other operational exchanges.

Following legislative amendments to the Financial Markets Act in 2016, exchange licences were issued to 4 Africa Exchange (4AX), A2X Markets (A2X), Equity Express Securities Exchange (EESE), and ZARX. Based on information available on the exchange websites, A2X has grown to become the second-largest venue since launching in October 2017, with a total market capitalisation of almost $356 billion and forty listings at the end of March 2021. In contrast, 4AX, EESE and ZARX had a combined market capitalisation of approximately $1.2 billion and twenty listed equities.

2.2 Domestic Inter-market Competition

Competition between exchanges is dictated by terms stipulated in the licences issued to the venues. Only the JSE, A2X and 4AX have full licences to trade across multiple asset classes, whereas the other venues are restricted to activity in equity markets[1]. Over and above the differences in licences, the new exchanges have strategically positioned themselves to serve distinct segments of the capital markets. Specifically, 4AX and ZARX cater to small companies looking to raise capital in the public markets but are unable to meet the JSE's onerous listing requirements, and EESE provides a platform solely for securities with ownership restrictions. A2X on the other hand was introduced as a venue for secondary listings, mainly for companies

[1] https://www.fsca.co.za/Regulated%20Entities/Pages/Licenses.aspx

already listed on the JSE. In essence, only the JSE and A2X compete directly for order flow and listings.

To date, there are 15 *large cap* (market capitalization $>$ R10 billion), 13 *mid-cap* ($<$ R10 billion and $>$ R1 billion) and 2 *small-cap* (R1 billion) JSE listed companies cross-listed on A2X. In addition to the equities, there are five JSE listed exchange-traded products (ETPs) available to trade, as stated on the venue's website. A2X has eight approved brokers[2], all of which are active at the JSE as well, including the JSE's five largest brokers as measured by value traded[3]. Both markets have identical continuous trading sessions, starting at 09:00 until 16:50. However, the JSE allows for intraday auctions and volatility auctions for securities that meet certain criteria. Furthermore, both exchanges operate order-driven, central order book trading systems with strict price-time priority.

When interrogating why a firm may choose to list on A2X, there are three factors worth considering: First, there is no additional regulatory burden placed on firms, as a secondary listing does not require any compliance over and above that which is required by the primary exchange. Second, there is no cost to list on A2X and neither are there any ongoing fees required to maintain a listing. And third, A2X has a simpler pricing model, which in principle should result in lower trade execution costs compared to the JSE[4].

[2] https://www.a2x.co.za/a2x-approved-brokers/

[3] https://www.jse.co.za/services/market-data/market-statistics

[4] The JSE uses a tiered model to determine equity trading fees in the central order book. Depending on the total value of the trade, fees range between 0.37bps and 0.48bps per trade with an upper limit of R439.74. On the other hand, passive orders on A2X's central order book will attract a fee of 0.20bps per trade, with a 100% discount, and aggressors are charged a flat fee of 0.40bps per trade with a ceiling limit of R355.00

Recognizing the significance of the microstructure changes brought about by the proliferation of trading venues, the Financial Sector Conduct Authority (FSCA) invited public commentary on a draft Conduct Standard for Exchanges in May 2020[5]. The main provisions of the regulations address the consequences of inter-market competition and the harmonisation of exchange rules. Standards for best execution practices are also put forward, as the legislation currently does not contain any provisions for trade execution quality. The draft defines best execution as "the duty of an authorised user to obtain the best possible result for a client when trading in securities on behalf of that client" (Financial Sector Conduct Authority, 2020, p. 2). Under the proposed framework, brokers would be required to have policies in place, describing how trades will be executed on favourable terms across multiple markets. Best execution considerations would include trading costs, speed of execution and liquidity in the market at the time of placing the order and execution. In essence, the draft Conduct Standard for Exchanges, calls for interoperability between exchanges to support coordination in the market. And it does so in a manner that can be likened to the measures already in place at other global financial centres.

For example, in the United States, the Intermarket Trading System enables interoperability between exchanges, allowing all eligible members to execute orders at any participating venue. In addition to the linked trading floors, National Best Bid and Offer (NBBO) regulations set by the Securities and Exchange Commission (SEC), prescribe trade execution at the best available quoted prices across all trading venues. In contrast, MiFID regulations in the European Union recognize that

[5] https://www.fsca.co.za/Regulatory%20Frameworks/Documents%20for%20Consultation/Draft%20Conduct%20Standard_Directive%20Exchanges.zip

inferring execution quality from costs alone is not entirely appropriate, because price is only one dimension. For this reason, brokers are required to further take into account any considerations relevant for the execution of an order, including but not limited to: order size, clearing and settlement fees and the likelihood of execution and settlement.

2.3 Regulation of Financial Institutions

One of the primary pieces of legislation governing activities of financial institutions is the Financial Sector Regulation (FSR) Act 9 of 2017. Following its introduction in April 2018, the FSR Act shifted the regulation of financial institutions from a fragmented approach with multiple stakeholders to a twin peaks model. The legislation established a new prudential regulator, the Prudential Authority (PA), and a new market conduct regulator, the Financial Sector Conduct Authority (FSCA). The FSCA has a broad mandate of ensuring efficiency and integrity in the South African financial sector. The PA, on the other hand, is tasked with microprudential oversight and operates within the South African Reserve Bank (SARB). Macroprudential oversight, and consequently the designation of SIFIs, is the responsibility of the SARB, in its capacity as the central bank. Currently, the designation of SIFIs is limited to only banks[6] and insurers[7]. The development of policies and procedures

[6] https://www.resbank.co.za/en/home/publications/publication-detail-pages/media-releases/2019/9303

[7] https://www.resbank.co.za/en/home/publications/publication-detail-pages/media-releases/2020/10294

to address the systemic importance of other non-bank financial institutions is still ongoing. Formal procedures to be followed before the designation prescribe an assessment of systemic risks using an indicator-based approach in line with the Basel Committee's recommendations. Broadly, systemic importance is evaluated based on: the institution's size, degree of interconnectedness, complexity, global activity and the extent to which the offered services are substitutable.

2.4 Interconnectedness and Concentration in the Financial System

South Africa's financial system is unmistakeably highly interconnected, largely due to the high degree of common exposure between institutions[8]. In the banking sector, for example, there are thirty-three licensed banks, however, the sector is dominated by five retail banks that account for approximately 90% of the sector's assets. In the insurance sector as well, five of the largest insurers account for close to 74% of sector assets. Data available on the asset allocations of money market funds[9] shows that almost 80% of their holdings are commercial bank-issued debt instruments. Furthermore, nearly 50% of collective investment scheme[10] assets are invested in domestic equities and 21% in bonds issued by financial institutions and the government.

[8] see https://www.resbank.co.za/en/home/publications/publication-detail-pages/reviews/finstab-review/2020/Second_edition_Financial_Stability_Review

[9] https://www.asisa.org.za/statistics/collective-investments-schemes/local-fund-statistics/

[10] Excluding interest bearing funds and hedge funds

The SARB has also identified interconnectedness between the financial sector and sovereign debt market as a significant threat to the stability of the financial system as a whole[11], as domestic financial institutions are large holders of sovereign debt. Almost 23% of total government bonds are held by domestic banks, while another 29% is held by insurers and pension funds collectively. For this reason, political uncertainty and deterioration in public finances are significant drivers of the perceived creditworthiness of financial institutions and how investors view risk in the capital markets.

[11]see https://www.resbank.co.za/en/home/publications/publication-detail-pages/reviews/finstab-review/2020/Second_edition_Financial_Stability_Review

Chapter 3

A Systemic Risk Analysis of South African Financial Institutions

3.1 Introduction

A financial crisis is classified as systemic if multiple institutions have failed simultaneously, or if the failure of a single institution has propagated across the system, causing the failure of other institutions (see Brownlees and Engle, 2017; Engle et al., 2015). A case in point is the global financial crisis that ensued following the collapse of Lehman Brothers in 2008; stock markets fell by 42% in the United States, 49% in the United Kingdom, 49% in Europe and 35% in Japan. Global GDP declined dramatically, and the IMF estimated that the total cost of the crisis was over \$11.9

trillion. Not too long after, in a somewhat similar turn of events, the collapse of African Bank in 2014 led to the unprecedented failure of ten money market funds, more than recorded anywhere in the world as a result of a single default. This single incident is estimated to have cost the South African economy close to $1 billion. A comprehensive understanding of the potentially devastating effects of systemic crises and financial contagion that follows requires an understanding of the concept of systemic risk.

Multiple definitions of systemic risk have been proposed in the literature, each one emphasizing a different aspect of the complexity of modern financial systems (for a comprehensive survey of the theories and empirical measures of systemic risk see Benoit et al., 2016). Broadly defined, systemic risk is the risk associated with the joint failure of institutions or markets that leads to the impairing of the intermediation process across a financial system. Central to the concept of systemic risk is the understanding that the failure of a systemically important institution often results in negative externalities, as it imposes significant costs on both the financial system and the wider economy.

High levels of interconnectedness and concentration in South Africa's financial sector raise several questions about, the systemic risk exposures, and contributions of financial institutions. An assessment of the extent to which concentration levels are reflected in sector risk contributions is carried out in this study, in which it is shown that the banking and insurance sectors are collectively the largest contributors to systemic risk. New evidence on the causal relationship between systemic risk in the banking sector and the prime lending rate is presented as well; in support of the view that systemic events in the financial sector have significant and adverse consequences for the broader economy. Fundamentally, this study complements the existing empirical assessments of financial stability in various jurisdictions, that have been recently examined in the literature.

In the global financial crisis of 2008, systemic risk propagated through common exposures, as firm failures put downward pressure on asset prices. Highly levered, debt-laden firms took one-way bets on housing prices, and when the housing market crashed, the interconnections between these firms led to a systemic crisis. Contagion was further exacerbated by the multitude of bilateral and multilateral financial contracts that American institutions were engaged in with global partners. Under normal market conditions, interconnectedness allows for more efficient intermediation and enhanced liquidity allocation (Moghadam and Vinals, 2010). In crisis conditions, however, those very interconnections may amplify shocks, creating excessive and unexpected risks. The moral hazard created by the anticipation of government bailouts also played a role in the severity of the crisis. In particular, the expectation of a government safety net encouraged excessive leverage and risk taking in good times, as institutions relied on their "too big to fail" status. While conventional microprudential measures may be sufficient to deal with such individual risks under normal circumstances, the system as a whole remains, or may be induced to be, fragile and vulnerable to systemic crises. The rapidity of the contagion in 2008 emphasized the fact that microprudential supervision alone is inadequate for maintaining the soundness of a financial system.

Among the many institutions at the forefront of the dialogue on establishing standards on the regulation of Systemically Important Financial Institutions (SIFIs) through the use of macroprudential policies have been the Basel Committee and the Financial Stability Board. Despite their efforts, conventional macroprudential regulations still face many challenges in capturing the complexity and interconnections of financial systems. For instance, introducing standards requires consensus on which characteristics make an institution more susceptible to system-wide shocks, or likely to propagate said shocks across the financial system. Further challenges are posed by the opportunities for regulatory arbitrage created by the imposition of thresholds when defining systemic importance using categorisation criteria. Recognizing this, researchers have since undertaken the task of bridging the gap between economic theory and regulatory practices.

There is an established body of literature concerned with the use of market-based measures of systemic risk to monitor financial stability in real-time and support prudential oversight (see Billio et al., 2012; Huang et al., 2009; Jobst and Gray, 2013; Lehar, 2005; Tarashev et al., 2010). Specifically, regarding the use of high-frequency measures designed to account for complexity and interconnections in the financial system, and the extent to which systemic risk is reinforced during times of distress. An emphasis is generally placed on measures that can identify SIFIs in time, and predict costs associated with their contributions to system-wide distress.

Admittedly, several such methods have been proposed in the literature, however, this study focuses specifically on the marginal expected shortfall (MES), and the conditional capital shortfall (SRISK) measures from the seminal work of Acharya et al. (2017) and Brownlees and Engle (2017). The aim is to investigate the usefulness of the aforementioned measures, in the real-time assessment of financial stability, and the development of systemic importance rankings, to augment existing supervisory processes in the South African financial system.

In the sections that follow, the study begins by reviewing the related literature outlining the main questions to be addressed. Section 3.3 then presents the data and outlines the econometric methods used to estimate systemic risk for 125 financial institutions, between 2003 and 2018. In Section 3.4 an empirical analysis of South Africa's financial sector is presented, addressing the research questions as they are described in Section 3.2.2. Section 3.5 summarises the findings.

3.2 Related Literature and Hypothesis Development

3.2.1 Measuring Systemic Risk

The widely accepted view is that there are three broad forms of systemic risk, namely: contagion risk, the risk of the abrupt unravelling of imbalances that have built up over time, and the risk of macro shocks causing simultaneous failures (see Brunnermeier and Oehmke, 2013; Jobst and Gray, 2013). There is however, as yet, no consensus on a concise definition of systemic risk. Differences in opinions regarding the definition are apparent in the various ways in which regulatory authorities around the world have addressed concerns around financial stability.

In the United States, the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 (Dodd-Frank Act) was enacted in response to the events that transpired during the global financial crisis of 2008. The Dodd-Frank Act calls for stricter prudential standards for SIFIs by granting regulatory agencies more authority to make sure financial institutions operate in a safe and stable environment (see Acharya, Cooley, Richardson, Walter, et al., 2010). A Financial Stability Oversight Council was established, with the mandate of identifying risks that could arise from the financial distress, failure, or ongoing activities of institutions within or external to the financial system, and as a result, compromise financial stability. In addition, the Dodd-Frank Act identifies characteristics that would warrant more stringent prudential standards for an institution, including the degree of the institution's leverage, the amount and types of its liabilities and financial assets, and the nature of its off-balance sheet exposures. Consideration is given to the nature, scope, size, scale, concentration and interconnectedness of the institution's activities as well. Fundamentally, the Act prescribes that systemic risks should be assessed and measured using classification-based criteria with distinct thresholds. Admittedly, this approach is not without its own flaws.

Acharya, Engle, and Richardson (2012) have previously discussed the downsides of measuring systemic risk using only categorization criteria, by highlighting several associated concerns. The primary contention is that supervision in this manner creates an incentive for regulatory arbitrage as institutions may set out to tick only the right boxes while retaining certain risk exposures. The frequency at which balance sheet information is made available poses further challenges when a timely and accurate assessment of the soundness of a financial system is required. Shortcomings of the classification-based measures have, as a result, called attention to the need for market-based metrics to support prudential oversight and inform policy decisions. Just as well, several authorities have made attempts at addressing these concerns in various ways.

The European Central Bank (ECB), for example, has highlighted four broad analytical approaches for the timely identification and accurate assessment of systemic risks[1] using continuously variable market information. First, financial stability indicators can be used to measure the contemporaneous state of distress and systemic stress. These can be direct indicators such as credit default swap (CDS) spreads. Second, the likelihood and severity of systemic events can be monitored using empirically calibrated early warning models designed to predict financial instability. Third, the resilience of the financial system can be evaluated by using macro-stress-testing models. The last approach suggests the use of contagion models to assess the cross-sectional transmission of instability. Central to each approach, is the consideration of the likelihood of, and the extent to which, the failure of one or several intermediaries or markets could lead to the failure of other intermediaries or markets. Most importantly, the proposed approaches demonstrate that supervisory frameworks can be adapted to include high-frequency, market-based indicators derived from analytical models.

On the question of what constitutes an appropriate market-based systemic risk measure, there is an understanding that any estimate, should in some way, account

[1] see ECB (2010)

for interconnections and how they are likely to exacerbate the rapidity of the financial contagion associated with systemic events. Several authors have sought out to identify such measures (Billio, Getmansky, Lo, and Pelizzon, 2012; Huang, Zhou, and Zhu, 2009; Jobst and Gray, 2013; Lehar, 2005; Tarashev, Borio, and Tsatsaronis, 2010). An index proposed by Lehar (2005) defines systemic risk as the probability that banks with more than a certain percentage of all bank assets become insolvent within a short period of time. In contrast, Huang et al. (2009) proposed a measure of systemic risk determined by a hypothetical insurance premium against financial distress, based on forecasted bank default probabilities and asset return correlations. Implied expected losses of financial institutions were used by Jobst and Gray (2013) to produce a measure of systemic solvency risk. Billio et al. (2012) put forward systemic risk measures predicated on relationships between equity market returns identified using various statistical methods, including Granger-causality and principal components analysis. Tarashev et al. (2010) contributed to the discussion around attribution through their novel use of cooperative game theory concepts to attribute various measures of system-wide risk to individual institutions. The literature has also emphasized that in addition to capturing the complexities of a financial system, the ideal systemic risk measure should be able to predict future levels of systemic risk. That being said, a shortcoming of the above mentioned measures is that they are not sufficiently forward-looking.

The usefulness of some measures for monitoring systemic risk in real-time has been evaluated as well (Acharya, Pedersen, Philippon, and Richardson, 2017; Adrian and Brunnermeier, 2016; Brownlees and Engle, 2017). The CoVar measure proposed by Adrian and Brunnermeier (2016) equates systemic risk contributions to the difference between the financial system's conditional value at risk (VaR) when an institution is, and is not, in distress. Evidence from Adrian and Brunnermeier's (2016) research shows that the CoVar measure would have predicted at least half of the covariances of financial institutions with the market, observed during the financial crisis in 2007. On the other hand, Acharya et al. (2017) put forward the systemic expected shortfall (SES) and the marginal expected shortfall (MES) as measures of systemic risk. MES is defined as the short-run expected equity loss conditional on the market being in distress. SES is a function of MES, described as a measure of how likely it is for an institution to be undercapitalized when the entire system is undercapitalized. In previous work, Acharya et al. (2012) explain that the intuition behind the use of capital shortfalls as a measure, is based on the fact that when an institution is undercapitalized, its ability to function as an intermediary is impaired. Under normal market conditions this void is easily filled by other institutions, however, during a crisis, when aggregate capital is also low, no institutions are available to step in. With that in mind, Acharya et al. (2017) demonstrate that both measures of systemic risk, would have predicted the losses realised during the financial crisis of 2007. Brownlees and Engle (2017) contribute further by setting up improved MES estimates that make use of time-varying conditional volatilities, time-varying correlations with a market index, and corresponding joint tail distributions.

Brownlees and Engle (2017) use the updated MES measures to estimate a firm's expected capital shortfall when the system is in distress, SRISK, and demonstrate that the measure can be aggregated to produce a measure of overall systemic risk.

Systemically important institutions would therefore be characterized by relatively large SRISK values as they would be the main contributors to under-capitalization in times of distress. An empirical analysis of systemic importance rankings implied by SRISK, in the United States over the financial crisis in 2007, correctly identified Frannie Mae, Freddie Mac, Morgan Stanley, Bear Sterns and Lehman Brothers as the largest contributors as early as the first quarter of 2005. In a single measure, characteristics such as size, leverage and interconnectedness, all of which are important drivers of systemic risk, are captured; consequently, SRISK and MES have gained notability as measures of systemic risk.

Previous empirical studies that have also made use of the MES and SRISK measures include Engle, Jondeau, and Rockinger's (2015) investigation of the extent to which industry groups, countries, and individual firms in the European financial system contribute to global systemic risk. Similarly, Bierth et al. (2015) made use of both MES and SRISK to measure the systemic risk contributions of insurers around the globe; to test their hypothesis that the systemic importance of insurers is driven, in part, by size and interconnectedness. More recently, Bostandzic and Weiss (2018) complemented the existing empirical literature by investigating if and why there are differences in the contributions of banks in the United States and Europe, to global systemic risk. However, there are certain limitations associated with the use of market-based measures. In particular, the measures are susceptible to noise and uncertainty in the market, which may in some instances provide misleading signals. Another inherent drawback is that some measures are likely to overlook the risk contributions of financial institutions for which conventional market data is unavailable. Nonetheless, these shortcomings do not detract from the utility that market-based measures have as tools for market supervision. Extensive work has gone into demonstrating that some systemic risk measures may be of use in monitoring macroeconomic conditions as well.

The view that systemic risk imposes negative externalities on the real economy has motivated many researchers to examine the relationship between systemic risk and indicators of macroeconomic activity (Allen, Bali, and Tang, 2012; Brownlees and Engle, 2017; Giglio, Kelly, and Pruitt, 2016). Allen et al. (2012) estimated aggregate systemic risk using CATFIN and demonstrate that the measure is able to forecast declines in the gross domestic product (GDP), industrial production and the unemployment rate. Giglio et al. (2016) also show that changes in systemic risk affect the distribution of shocks to industrial production and other indicators of macroeconomic activity in the United States and Europe. Similarly, Brownlees and Engle (2017) document that aggregate SRISK forecasts lower industrial production and greater unemployment rates.

3.2.2 Hypothesis Development

As was mentioned earlier, the South African financial system has generally been dominated by large highly interconnected institutions facing little competition[2] throughout its history. The banking sector for instance, where only five institutions account for approximately 90% of the sector's assets, was reported at the end of 2020 to have

[2] https://www.resbank.co.za/en/home/publications/publication-detail-pages/reviews/finstab-review/2020/Second_edition_Financial_Stability_Review

a Gini index of 84 and a Herfindahl-Hirschman Index of 0.2; indicative of unequally distributed value in a borderline anti-competitive environment. This apparent lack of competition and diversity is prevalent in other sectors as well, although not as pronounced; including the insurance sector, where the five largest institutions account for approximately 74% of the sector's assets. Empirical evidence of the collective systemic significance of banks and the relevance of an institutions size when measuring systemic risk contributions has previously been provided by Borri and di Giorgio (2021) and Engle et al. (2015). Given the prevailing market structures, it can be conceivably hypothesized that the concentration levels are likely to be reflected in the systemic risk contributions.

Hypothesis 3.1 *Banks and insurers are the largest contributors to systemic risk in South Africa's financial sector.*

The other main question addressed by this study pertains to the impact systemic risk has on macroeconomic conditions. In particular, one of the ways in which capital shortfalls have been hypothesised to spill over into the real economy is through lending. For example, when in distress and attempting to preserve capital, financial institutions may often opt to reduce their lending activity to both other institutions and consumers by increasing interest rates. This view is supported by Ivashina and Scharfstein's (2010) evidence of a substantial reduction in lending activity, during the global financial crisis of 2008, that originated from the supply side. More recently, Silva et al. (2018) also demonstrated how distressed banks may propagate stress to the interbank lending network, resulting in banks reducing their exposure to loans through credit rationing. Building upon this notion, the following hypothesis is tested.

Hypothesis 3.2 *Systemic risk has a causal effect on interest rates.*

The evidence reviewed so far has highlighted the shortcomings of conventional macroprudential used to monitor SIFIs and the various ways in which academics and practitioners have attempted to address these concerns. Despite the problem being well understood, it is widely accepted that no single measure can fully capture all the complexities that may have a bearing on an institution's systemic importance. That being said, two important themes emerge from the evidence available to date: first, the degree of interconnectedness and concentration in a financial system influences not only the levels of systemic risk but also how it is distributed between firms. And second, systemic events in the financial sector have significant, and adverse consequences for the broader economy.

3.3 Data and Methodology

3.3.1 Data

The panel dataset used consists of 125 JSE listed financial institutions, for which daily equity prices and balance sheet data are collected from Bloomberg, over the 16 years starting in January 2003 through to December 2018. Note that balance sheet values are assumed to remain constant in between reporting dates. A breakdown of the dataset shows that it constitutes of seven banks, nine insurers, twenty-four asset managers and investment related service providers, sixty-one real estate investment trusts and twenty-four financial services providers. Market performance is measured using the JSE's Financial 15 Index (FINI 15), a widely accepted indicator of performance in the financial sector. Additional data sources include the SARB's website, from which historical interest rates are retrieved. Only the prime lending is considered, as this is the benchmark rate at which banks lend out to the public.

3.3.2 Model Specification

Estimating the Marginal Expected Shortfall

Following Brownlees and Engle (2017), MES is defined as the short-run expected equity loss conditional on market losses being greater than C, a threshold defined by the market's Value-at-Risk (VaR) at $\alpha\%$[3]. The first step involved in estimating the MES requires modelling the bivariate process of firm and market returns:

$$\begin{aligned} r_{m,t} &= \sigma_{m,t}\varepsilon_{m,t}, \\ r_{i,t} &= \sigma_{i,t}\varepsilon_{i,t} \\ &= \sigma_{i,t}\rho_{i,t}\varepsilon_{m,t} + \sigma_{i,t}\sqrt{1-\rho_{i,t}^2}\xi_{i,t}. \end{aligned}$$

The log returns of the market index and the equity of firm i at time t are, $r_{m,t}$ and $r_{i,t}$ respectively. Similarly, $\sigma_{m,t}$ and $\sigma_{i,t}$ are the market and firm volatilities, and $\rho_{i,t}$

[3] VaR_α is the greatest loss that can be expected with confidence $1-\alpha$, i.e. $Pr(R < VaR_\alpha) = \alpha$

is the correlation between $r_{m,t}$ and $r_{i,t}$. It is assumed that the disturbances $\varepsilon_{m,t}$ and $\xi_{i,t}$ are i.i.d. over time, with zero mean, unit variance and zero covariance, under an unspecified distribution. Using the above quantities, gives the following definition of MES:

$$\begin{aligned} MES_{i,t-1} &= E_{t-1}\left(r_{i,t}|r_{m,t} < q_{\alpha,t-1}(r_t) = C\right) \\ &= \sigma_{i,t}E_{t-1}\left(\varepsilon_{i,t}|\varepsilon_{m,t} < \frac{C}{\sigma_{m,t}}\right) \\ &= \sigma_{i,t}\rho_{i,t}E_{t-1}\left(\varepsilon_{m,t}|\varepsilon_{m,t} < \frac{C}{\sigma_{m,t}}\right) + \sigma_{i,t}\sqrt{1-\rho^2_{i,t}}E_{t-1}\left(\xi_{i,t}|\varepsilon_{m,t} < \frac{C}{\sigma_{m,t}}\right). \end{aligned} \tag{3.1}$$

Next, using an approach outlined by Brownlees and Engle (2017, 2012), time varying conditional correlations are estimated using a dynamic conditional correlation (DCC) model, conditional stochastic volatilities are estimated using a generalized autoregressive conditional heteroskedasticity (GARCH) model, and the tail expectations using a non-parametric kernel estimator. The following asymmetric Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) specification is used to estimate the conditional volatilities of the equity returns:

$$\sigma^2_{m,t} = \omega_m + \alpha_m r^2_{m,t-1} + \gamma_m r^2_{m,t-1}\mathbb{I}_{r_{m,t}<0} + \beta_m \sigma^2_{m,t-1}$$

$$\sigma^2_{i,t} = \omega_i + \alpha_i r^2_{i,t-1} + \gamma_i r^2_{i,t-1}\mathbb{I}_{r_{i,t}<0} + \beta_i \sigma^2_{i,t-1}.$$

The conditional volatilities of the market index and the equity of firm i at time t are $\sigma^2_{m,t}$ and $\sigma^2_{i,t}$ respectively. As it is known that negative leverage shocks have a greater impact on volatility than positive shocks (see Alexander, 2008), the indicator variables $\mathbb{I}_{r_{m,t}<0}$ and $\mathbb{I}_{r_{i,t}<0}$ allow the model to capture the asymmetric effects of leverage on volatility. This GJR-GARCH specification accounts for the effects of volatility clusters as well; relatively large values of β_m and β_i indicate that volatility will persist following a crisis in the market, regardless of anything happening in the market (see Alexander, 2008). Note that Gaussian standardized errors are used, in line with Brownlees and Engle (2012) and Idier et al. (2014). An allowance is made for possible asymmetries in the time varying conditional correlation between the equity and market returns by using a modified DCC approach proposed by Cappiello et al. (2006). Details on the DCC procedure and the non-parametric kernel estimator are available in Appendix A.

Estimating SRISK

In general, a firm's capital shortfall —capital reserves held by a firm for regulatory and prudential reasons, in excess of the firm's equity value —is equivalent to the following quantity:

$$\mathbf{CS}_{i,t} = k\mathbf{A}_{i,t} - \mathbf{E}_{i,t} \ = k\left(\mathbf{L}_{i,t} + \mathbf{E}_{i,t}\right) - \mathbf{E}_{i,t}.$$

$\mathbf{E}_{i,t}$ and $\mathbf{L}_{i,t}$ are the market value of equity and the book value of debt of firm i at time t, respectively. The implied value of the firm's assets is $\mathbf{A}_{i,t}$ and k is the prudential capital fraction. When a firm is in distress this quantity will be positive, indicating insufficient working capital, whereas a negative value signals a capital surplus. Conditional capital shortfall on the other hand, or SRISK, is a measure of the expected capital shortfall of a firm conditional on a systemic event. Following

Brownlees and Engle (2017), defining a systemic event as a market decline greater than C over h periods, gives:

$$\begin{aligned} SRISK_{i,t} &= E_t\left(\mathbf{CS}_{i,t+h}|r_{m,t+1:t+h} < C\right) \\ &= kE_t\left(\mathbf{L}_{i,t+h}|r_{mt+1:t+h} < C\right) - (1-k)E_t\left(\mathbf{E}_{i,t+h}|r_{m,t+1:t+h} < C\right). \end{aligned}$$

If $h = 1$, it is easy to see that $E_t\left(\mathbf{E}_{i,t+1}|r_{m,t+1:t+1} < C\right)$ is equivalent to $\mathbf{E}_{i,t}(1 - MES_{i,t})$ i.e. the market value of equity multiplied by the expected one period equity devaluation, conditional on a market return indicative of a systemic event. Generalizing this relation to a distress scenario lasting h periods requires consideration to be given to multi-period equity returns, such that

$$E_t\left(\mathbf{E}_{i,t+h}|R_{mt+1:t+h} < C\right) = \mathbf{E}_{i,t}(1 - LRMES_{i,t}),$$

where $LRMES_{i,t}$ is the Long-Run MES i.e. the expected equity loss in a distress scenario lasting h periods, conditional on a market decline indicative of financial distress. Here, LRMES is estimated without simulation[4], such that it is equivalent to $1 - \exp(\log(1-d) \times DCbeta_{i,t})$[5], where d is the six-month crisis threshold for the market index decline and $DCbeta_{i,t}$ is the firm's dynamic conditional beta coefficient. Furthermore, it is assumed that debt cannot be renegotiated when a systemic event

[4]In general, a closed form solution for $LRMES$ is not available. However, it is possible to implement Monte-Carlo simulations such that $LRMES$ is given by the Monte-Carlo average of the simulated h period returns.

[5]Brownlees and Engle (2017) propose three different approaches for estimating MES. None of these alternative are considered. Instead, the definition provided by The Volatility Laboratory (V-Lab). See https://vlab.stern.nyu.edu/docs/srisk/MES

occurs i.e. $E_t \left(\mathbf{L}_{i,t+h} | r_{m,t+1:t+h} < C \right) = \mathbf{L}_{i,t}$. In contrast to earlier studies, the prudential capital fraction, k, is a time-varying quantity determined by the minimum total capital plus Pillar 2A[6] requirements stipulated in Annexure B of Directive D4/2020[7] issued by the SARB. Lastly, the quantities α and d are set to 5% and 40% respectively. Put simply, SRISK is estimated using the following equation

$$SRISK_{i,t} = k_t \mathbf{L}_{i,t} - (1 - k_t) \mathbf{E}_{i,t} \left(1 - LRMES_{i,t} \right). \tag{3.2}$$

In an ecosystem made up of N institutions, a broad measure of financial distress can be obtained by aggregating $SRISK$ across all N institutions.

$$SRISK_t = \sum_{i=1}^{N} \left(SRISK_{i,t} \right)_+, \tag{3.3}$$

where $(x)_+$ denotes $max(x, 0)$. Capital surpluses are explicitly ignored as it is unlikely that they will easily be mobilized during a crisis to cover any shortfalls in the system, and support failing firms through acquisitions or loans. It is this breakdown in financial intermediation that has been hypothesized to result in adverse consequences for the broader economy. In essence, $SRISK_t$ provides an estimate of the undercapitalization that the system as a whole will face during a crisis. SIFIs can therefore be identified by the extent to which they contribute to system wide capital shortfall during a crisis, such that a firm's contribution to overall systemic risk is

[6] Pillar 2A is an additional systemic risk capital requirement introduced on 1 January 2013. The quantity is revised annually by the PA and is capped at 2%. Prior to 2013, k is fixed at 8% for all firms, in line with previous studies and the Basel Accords.

[7] https://www.resbank.co.za/en/home/publications/publication-detail-pages/prudential-authority/pa-deposit-takers/banks-directives/2020/10202

given by

$$SRISK\%_{i,t} = \frac{\left(SRISK_{i,t}\right)_+}{\sum_{i=1}^{N}\left(SRISK_{i,t}\right)_+}. \tag{3.4}$$

3.4 Results

Turning now to the empirical evidence, a time series plot of SRISK aggregated across all firms is presented in Figure 3.1. Note that the dates corresponding to the introduction of the Pillar 2A requirements, and the enactment of the FSR Act are highlighted in the figure. In general, the average level of the measure appears to have increased over time. The elevated levels of SRISK between 2008 and 2010 highlight the severity of the contagion during the global financial crisis. Notwithstanding the crisis periods, what stands out from Figure 3.1, is that the average level of SRISK before the introduction of the Pillar 2A requirements is lower than in subsequent periods. An unsurprising result as well, given that SRISK is an increasing function of the prudential capital fraction, as can be seen in Equation 3.2. An interesting observation is the dramatic increase that occurred in late 2015. The elevated SRISK levels recorded over this period coincide with a political scandal that led to significant increases in bond yields, and a depreciation of the currency. This result supports the SARB's opinion that interconnectedness between the financial sector and sovereign debt market is a significant threat to financial stability. It is also worth noting that, a direct consequence of the exclusion of capital surpluses in estimating SRISK, is that the number of firms contributing to the aggregate measure varies throughout the period under investigation. Some firms frequently fall in and out of the purview of the model as they record capital surpluses when markets react to new information. In fact, of the 125 firms in the sample only thirty-three unique firms, contributed to aggregate SRISK at some point in the sample period. Another interesting observation is that the average number of contributing firms increased with time.

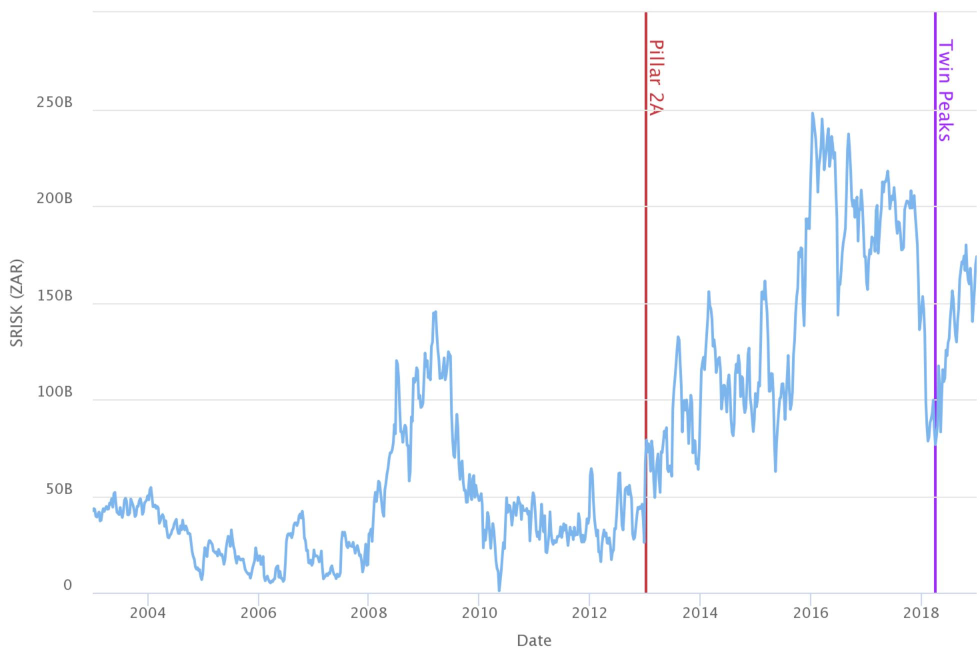


Figure 3.1. Aggregate SRISK. This figure plots SRISK estimated daily over the sixteen year period starting in January 2003. The sample consists of 125 financial institutions listed on the Johannesburg Stock Exchange. Daily SRISK values are calculated for each institution and aggregated across only the institutions with positive estimated values i.e. capital shortfalls. The vertical lines mark changes in the regulatory environment related to the enforcement of Pillar 2A requirements, and the implementation of the twin peaks model.

Further analysis reveals that, collectively, banking institutions are generally the largest contributors to aggregate SRISK. Figure 3.2 reports SRISK contributions after grouping firms into five sectors defined by the Industry Classification Benchmark (ICB). Significant contributions by the banking sector are expected for two reasons;

first, banks typically exhibit the highest levels of leverage relative to other financial institutions and therefore have greater exposure to capital shortfalls in times of distress. Second, the market for financial services in South Africa is generally dominated by large highly interconnected institutions facing little competition. It therefore comes as no surprise that the "Big-four" banks— FirstRand, Nedbank, Absa Group and Standard Bank— are some of the largest contributors to SRISK, in line with the view that large institutions are more likely to be systemically important. What stands out as well is that Standard Bank is, on most days, the top contributor to aggregate SRISK; confirming that the largest bank is also the most systemically important financial institution. The size of the banking sector's contribution has however decreased over time, as the capital shortfalls estimated for insurers and asset managers have increased. Note that the apparent increase in the contributions of the insurance sector leading up to the crisis in 2008 can be attributed to a decrease in the SRISK of banking institutions, as SRISK in the insurance sector was relatively stable over that period. From Figure 3.2, it can also be seen that there is limited evidence of capital shortfalls in the real estate and financial services sectors throughout the sample period. Moreover, the results indicate that there were no significant spillovers from the global financial crisis into either of these sectors. In fact, over the duration of the crises, none of the institutions in the real estate sector recorded capital shortfalls; there was however a decline in the aggregate level of capital surpluses between 2007 and 2009 as observed in unreported results.

The value-weighted average MES of all 125 financial institutions is presented in Figure 3.3. In contrast to SRISK, notwithstanding the crisis periods, the average level

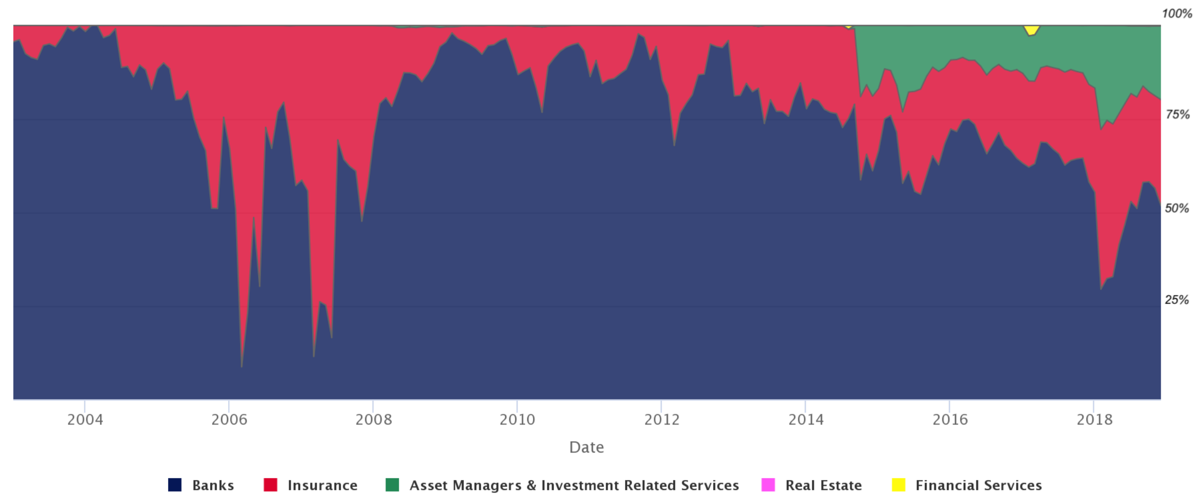


Figure 3.2. ICB sector percentage SRISK contributions. This figure plots the percentage SRISK contributions after grouping all JSE listed financial institutions into one of five ICB sectors. The sample of 125 firms spans the sixteen year period starting in January 2003, and consists of Banks(7), Insurers(9), Asset Managers & Investment Related Services(24), Real Estate(61) and Financial Services(24). Contributions are calculated by dividing the total SRISK for all firms in each sector by aggregate SRISK, and then averaging across all trading days in a month.

of MES appears to have remained relatively stable over time. Leading up to the crisis in 2008, MES is observed to have started increasing as early as in 2006. Just as well, the measure increased over the period of market turmoil in late 2015. Furthermore, there is a clear increase in early 2018, surrounding the adoption of the twin peaks regulatory approach mandated by the FSR Act. Unreported results indicate that relative to all other sectors, the banking sector generally has the largest MES values, followed by the insurance sector. In addition to being smaller in magnitude, average MES values of the asset management and real estate sectors are less volatile compared to the other sectors.

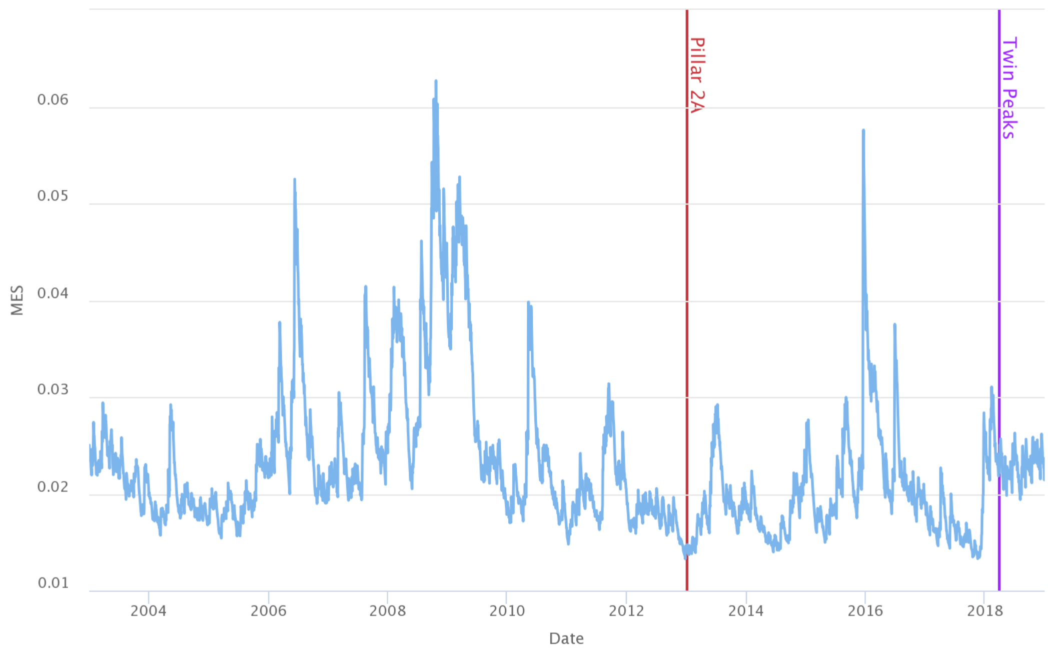


Figure 3.3. Daily value-weighted MES. This figure plots the value-weighted MES of 125 JSE listed financial institutions over the sixteen year period starting in January 2003. MES is defined as the short-run expected equity loss conditional on the market taking a loss greater than its Value-at-Risk (VaR) at $\alpha\%$, set as the 95% quantile of the empirical distribution of the JSE's Financial 15 index (FINI 15). Daily MES values are calculated for each institution and weighted by daily market capitalization. The vertical lines mark changes in the regulatory environment related to the enforcement of Pillar 2A requirements, and the implementation of the twin peaks model.

3.4.1 Interconnectedness Between Sectors

Given the highly interconnected and concentrated market structures, one question that needs to be asked is whether non-bank and non-insurance financial institutions actually contribute to systemic risk, or whether they bear the brunt of the externalities created by systemic risk in the banking and insurance sectors. The information presented in Figure 3.2 seems to support the latter argument, however, a conclusion can only be made after examining the question of causality. To determine if, and how, changes in systemic risk are propagated across sectors the following predictive regression model is estimated:

$$\Delta logSRISK_{t+1}^{i} = \alpha_0 + \alpha \Delta logSRISK_t^i + \beta \Delta logSRISK_t^j + \upsilon_t,$$

where $\Delta logSRISK_t^i$ is the natural logarithm of the daily growth rate of aggregate SRISK in sector i at time t, $\Delta logSRISK_t^j$ is the natural logarithm of the daily growth rate in sector j, and υ_t is an error term. If β is significantly different from zero, SRISK changes in sector j can be used to forecast changes in sector j. On that basis, positive regression coefficients would provide evidence of spillover effects. Non-bank and non-insurance sectors are studied collectively; as can be seen from Figure 3.2, each of these sector's SRISK values are not sufficiently variable to allow meaningful analysis of changes throughout the sample period.

Table 3.1. Pairwise sector SRISK predictive regressions.
This table presents the results of the pairwise predictive regressions estimated for the Banking (BN), Insurance (IN) and Non-bank and insurance (NBI) sectors. The i, j entry of the table reports the estimated β coefficient in the equation $\Delta logSRISK_{t+1}^{i} = \alpha_0 + \alpha \Delta logSRISK_t^i + \beta \Delta logSRISK_t^j + \upsilon_t$. Robust standard errors are shown below their respective coefficients. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively

	$SRISK^{BK}$	$SRISK^{IN}$	$SRISK^{NBI}$
$SRISK^{BK}$		0.0226 (0.0265)	−0.0064 (0.0140)
$SRISK^{IN}$	−0.0249* (0.0150)		−0.0257 (0.0181)
$SRISK^{NBI}$	−0.0404* (0.0243)	−0.0755 (0.0695)	

Contrary to expectations, most of the β coefficients reported in Table 3.1 are negative. The estimation results indicate that in general, an increase in SRISK in one sector, predicts a decrease in SRISK in another sector. To put it another way, the evidence seems to suggest that increases in SRISK are not propagated across sectors, despite the financial sectors as a whole being characterised by strong interconnections. Furthermore, it appears that only changes in the banking sector are significant predictors of changes in the other sectors. This may be a consequence of the fact that banking institutions are generally significantly larger.

3.4.2 Rankings Comparison

Indicator-based measures are among the most widely used methods of assessing an individual institution's systemic importance. An assessment of the extent of the similarity between the systemic importance rankings implied by SRISK and MES, and those implied by a set of firm characteristics is carried out in this section. The characteristics considered are the institution's size, leverage and the value of its financial obligations; it is a widely held view that there is a positive association between systemic importance and each of these quantities. Size is measured as the institution's market capitalization; debt is defined as the book value of the institution's liabilities; the degree of leverage is equivalent to the debt to equity ratio. Spearman rank correlation coefficients used to assess the strength and direction of association between SRISK and MES, and the firm characteristics are presented in Table 3.2.

All the Spearman rank correlation coefficients are found to be positive and statistically significant. Table 3.2 shows that, relative to the other indicators, debt has the strongest association with both systemic risk measures, followed by firm size. In contrast to earlier findings, the rank correlation between SRISK and leverage is not as strong as the other indicators. In particular, similar tests by Brownlees and

Table 3.2. Rank correlations with Size, Debt and Leverage.
This table reports estimates of Spearman rank correlations between the estimated systemic risk measures and a set of firm characteristics generally accepted indicators of systemic importance. Correlations are estimated using values sampled at the end of each year in the sample period. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively

	Firm characteristics		
	Size	Debt	Leverage
SRISK	0.6951***	0.7688***	0.3428***
MES	0.7482***	0.7593***	0.2510***

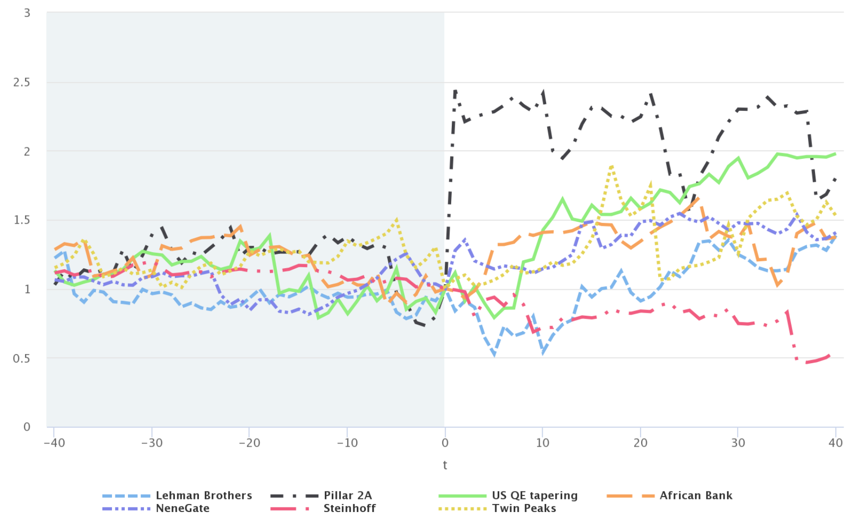
Engle (2017) found that for a sample of U.S. financial institutions, leverage generally has higher rank correlations than all other firm characteristics; although, it is worth noting that the magnitude of the leverage rank correlation reported in Table 3.2 is consistent with their findings. The reason for this is not clear, but it might be related to how value is distributed across the financial sector.

Having shown that systemic importance implied by the estimated measures is generally consistent with established indicators, the next step in demonstrating the usefulness of SRISK and MES is an assessment of the sensitivity of the measures to market events

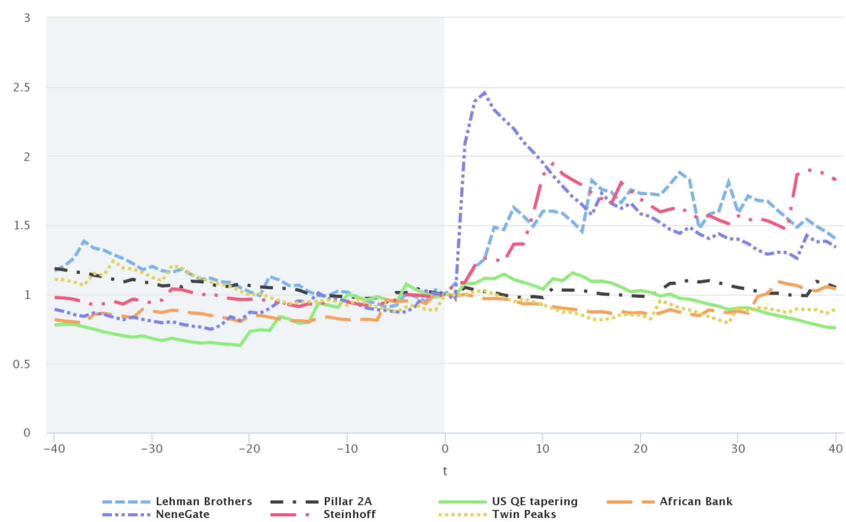
3.4.3 Sensitivity to Market Events

As was discussed in Section 3.2.1, challenges are posed by the frequency at which balance sheet information is made available. Consequently, accounting-based indicators cannot be fully relied on to provide accurate, forward-looking, and timely assessments of financial stability. In contrast, market-based measures, by definition, are forward-looking since they account for the changing expectations of market participants immediately after they are reflected in prices. Market-based measures are therefore more suitable for monitoring financial stability in real-time. To examine how shocks to the financial system affect SRISK and MES, and how promptly the measures adapt to prevailing market conditions, the following significant events in the sample period are considered.

- September 15, 2008: Lehman Brothers' files for Chapter 11 bankruptcy protection, making this the largest bankruptcy filing in United States history
- January 1, 2013: Pillar 2A capital requirements come into effect
- June 19, 2013: United States Federal Reserve (FED) announces tapering of quantitative easing (QE) policies intended to stimulate the economy after the global financial crisis
- August 10 2014: The SARB announces that African Bank is to be placed under curatorship with immediate effect. This single default subsequently led to the unprecedented failure of ten money market funds.
- December 9, 2015: 'NeneGate' - South Africa's Finance Minister is abruptly dismissed. In the two days that followed, the top seventeen publicly traded financial and real estate companies lost over $19 billion in value
- December 6, 2017: Steinhoff announces investigation into accounting irregularities. Following this announcement, Steinhoff lost a record 62% of its market capitalization in a single day of trading and in the days that followed, the sell-off induced a loss of more than 95% of the firm's value, wiping out more than $20 billion in value.
- April 1, 2018: Twin peaks regulatory structure implemented, effectively increasing scope and influence of prudential authorities.



(a). Daily SRISK values around the significant market events.



(b). Daily MES values around the significant market events.

Figure 3.4. This figure shows the daily aggregate SRISK and average MES over the sixty days before and the sixty days after each of the identified shocks. The sample consists of 125 financial institutions listed on the Johannesburg Stock Exchange. Daily SRISK values are calculated for each institution and aggregated across only the institutions with positive estimated values i.e. capital shortfalls. Daily MES values are calculated for each institution and averaged across the entire sample. The values shown here are indexed relative to t_0

Tests for structural breaks in the aggregate SRISK and average MES are carried out over the eighty trading day windows— approximately four calendar months— centred around the respective event dates. Time series plots of aggregate SRISK and value-weighted MES relative to the event date are presented in Figures 3.4a and 3.4b respectively. As there is no reason to assume that the event and structural break dates will always coincide, in each instance, the supremum-Wald test (Andrews, 1993) is used to test for instability over a range of possible dates relative to the event. A summary of dates on which structural breaks are estimated to have occurred is shown in Table 3.3.

Table 3.3. Supremum-Wald tests for structural breaks in SRISK.
This table presents a summary of the results of a series of tests of breaks in the long run mean SRISK in the days surrounding a series of economically significant events. The supremum Wald test, tests for structural breaks over a range of possible break dates. The second and fifth columns of the table report the time, in days relative to the event date, at which the breaks are estimated to have occurred. The table also reports pre and post break averages for both estimated measures. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively

	SRISK			MES		
	Break time	Pre-break avg	Post-break avg	Break time	Pre-break avg	Post-break avg
Lehman Brothers	25^{***}	81.52	112.23	5^{***}	0.0370	0.0543
Pillar 2A	1^{***}	41.88	73.29	-19^{***}	0.0154	0.0143
US QE tapering	27^{***}	82.09	130.16	-17^{***}	0.0179	0.0247
African Bank	5^{***}	96.06	114.44	-6^{***}	0.0148	0.0165
NeneGate	14^{***}	175.93	238.44	2^{***}	0.0213	0.0385
Steinhoff	3^{***}	195.94	138.21	9^{***}	0.0148	0.0246
Twin peaks	28^{***}	88.58	111.14	-22^{***}	0.0284	0.0228

The supremum-Wald tests provide strong evidence of structural breaks in the periods surrounding the significant market events. However, it is also apparent from Table 3.3 that these breaks do not coincide with their respective events. Instead, SRISK structural breaks are observed one to twenty-eight trading days after the event dates. In contrast, MES structural breaks generally occur before the respective SRISK breaks, between the periods t_{-22} and t_5. Furthermore, in each instance, the null hypothesis of no structural breaks is rejected at the 1% critical level.

An interesting observation to emerge from the data is that, for events relating to changes in regulatory environment— Pillar 2A and Twin peaks— SRISK is on average greater in the post-break period, however, MES not only declines but the breaks are also reported to have occurred before the event dates. Evidence regarding the effects of institutional failures— Lehman Brothers, African Bank and Steinhoff— indicates that both SRISK and MES are generally greater in the post-break period. An exception, however, is the decline in SRISK following the Steinhoff incident, where SRISK is reported to decline in the post-break period. This inconsistency may be due to fact that the incident occurred outside the financial sector; instead, it may be that the financial institutions were only affected indirectly, through instability in the broader economy, as reflected in the higher MES values. Sensitivity of the measures to systemic events and policy changes in foreign jurisdictions is demonstrated by the changes following the Lehman Brothers bankruptcy and the QE announcement by the FED. The results presented in Table 3.3 also provide further support for the view that interconnections between the financial sector and sovereign debt market pose a significant threat to stability in South Africa's financial system.

Although SRISK and MES appear to correctly identify systemically important financial institutions and respond accordingly to significant market events, the predictive power and accuracy of the measures remain questionable. In the case of African Bank, for example, unreported results show that there is limited evidence of the bank having positive SRISK values prior to its failure. Just as well, MES rankings do not provide unambiguous evidence of the bank's systemic importance leading up to the SARB's announcement. Significant changes in both measures are observed only in the three days before the event date. In just a short space of time, African Bank became the sixth most systemically important institution, contributing approximately 7% of aggregate SRISK, and the bank's MES increased almost twenty-six times in magnitude. Another interesting observation is that the model estimated a capital shortfall of approximately R5.7 billion for African Bank, however, the subsequent simultaneous failure of ten money market funds brought the total cost of this single event to R10 billion, almost twice the estimated amount. This discrepancy is likely related to the fact that money market funds are beyond the scope of the SRISK model that relies on equity market data. From a different perspective, it could be argued that costs were exacerbated by interconnections that may not have been adequately captured by the model. Nonetheless, it is clear that there is a need to account for associated costs of financial institutions outside of public markets, even in instances where the financial sector's value is concentrated in exchange listed institutions. The aforementioned limitations, however, do not negate the view that there is a benefit to augmenting supervisory functions with the measures. In fact, the usefulness of SRISK in particular has been found to extend beyond monitoring financial stability, in predicting macroeconomic conditions.

3.4.4 SRISK and the Macroeconomy

Moving on to Hypothesis H3.2, an examination of the interrelationship between SRISK in the banking and non-banking sectors, and the prime lending rate is carried out in this section. Specifically, the Granger-causality testing procedure outlined by

Toda and Yamamoto (1995)[8] is used to interrogate whether SRISK in the banking sector can be used to forecast interest rates, and how interest rates interact with systemic risk in the non-banking sectors.

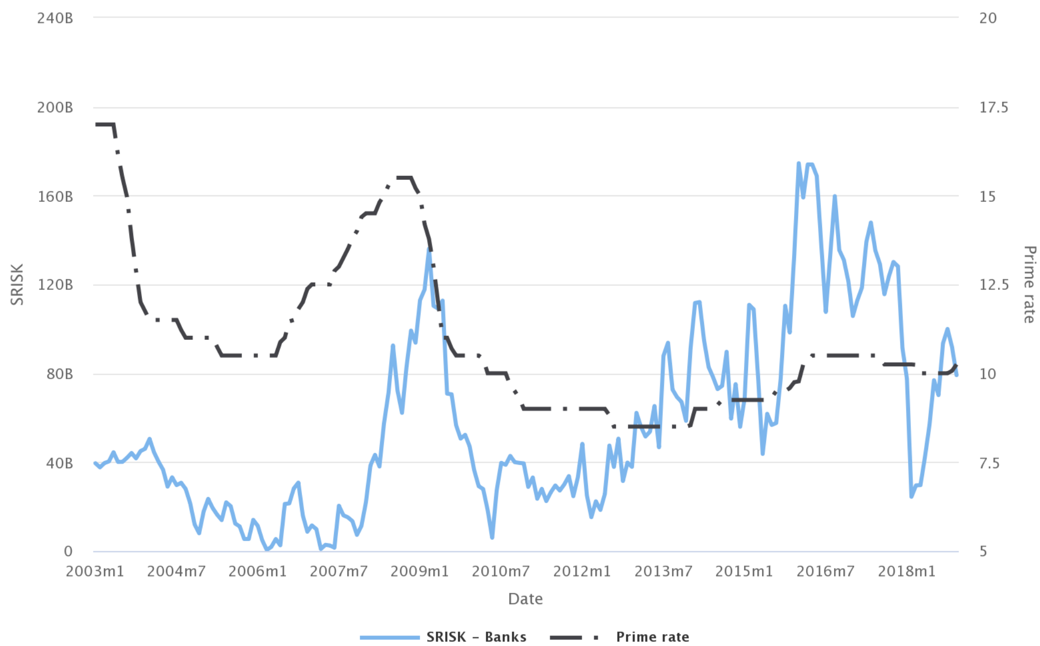


Figure 3.5. Banking sector SRISK and the prime lending rate. This figure shows the monthly average of SRISK in the banking sector and the prime lending rate over time.

A time series x, Granger-causes another time series y, if lagged values of x have statistically significant coefficients in a regression of y on lagged values of itself and x (see Greene, 2003; Stock and Watson, 2015). In principle, where the causality conditions are satisfied, it can be argued that future values of y can be predicted by past values of x. The information shown in Figure 3.5 suggests that a causal relationship may exist between aggregate SRISK in the banking sector and the prime lending rate, as it illustrates a similarity in the pattern and timing of changes.

[8]The procedure allows for causality testing irrespective of the order of integration of the processes

Table 3.4. Tests for causality between SRISK and interest rates.
This table presents the results of tests for Granger causality between SRISK and the prime lending rate using the Toda and Yamamoto (1995) procedure. Augmented Dickey-Fuller tests show that the maximum order of integration for the group of time series, m, is 0. Vector autoregressive (VAR) models with maximum lag length $p_{banks} = 5$ and $p_{non-banks} = 8$ are suggested by lag order selection statistics (AIC). Lagrange multiplier tests for serial independence find that the residuals are serially correlated in both instances. The autocorrelation is removed when the maximum lag lengths are increased to $p_{banks} = 10$ and $p_{non-banks} = 14$. Both models also satisfy the eigenvalue stability condition. The final VAR models includes m additional lags of each of SRISK and the lending rate as exogenous variables. For each equation in the VAR models, the hypotheses that the coefficients estimated for the endogenous variable and all its lags are jointly zero are tested i.e. the dependent variable is not Granger-caused by the endogenous variable. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively

	Wald statistic	**p-Value**
H_0: Bank SRISK does not Granger-cause the prime rate	20.19	0.028
H_0: The prime rate does not Granger-cause bank SRISK	13.97	0.175
H_0: Non-bank SRISK does not Granger-cause the prime rate	12.32	0.581
H_0: The prime rate does not Granger-cause non-bank SRISK	36.93	0.001

The results of the pairwise Granger causality tests are reported in Table 3.4. From the table, it can be seen that aggregate SRISK in the banking sector can be used to forecast the prime lending rate. This result complements previous findings on the implications of systemic risk for the real economy; including a study by Allen et al. (2012) that demonstrated that high levels of systemic risk in the banking sector impact lending activity by reducing the value of aggregate loans. Interestingly, it appears that the prime lending rate can, in turn, be used to forecast aggregate SRISK in the non-banking sectors. A similar phenomenon was previously documented by Engle et al. (2015) and De Nicolò and Lucchetta (2011, 2012) as well. Specifically, their evidence reveals some feedback effects from macroeconomic variables— including industrial production, inflation and unemployment indices— to SRISK. It is also worth noting that the Wald statistics indicate that neither of the significant causal relationships is symmetric i.e. significant causality in the opposite direction as well. Taken together, these results point to the possibility of interest rates being a contagion channel for systemic risk spillovers from the banking sector.

3.5 Summary

Daily MES and SRISK values are estimated for a panel of 125 South African financial institutions. The sample period covers the sixteen years starting in January 2003 through to the end of 2018. Evidence shows that the banking sector is the single largest contributor to systemic risk, making up more than 50% of the aggregate SRISK throughout the sample period. This contribution has however decreased over time, as expected capital shortfalls in the other sectors have increased. Contrary to previous literature, our results suggest that increases in SRISK are not propagated across sectors, as indicated by the negative coefficients estimated in pairwise predictive regressions. Additional checks are carried out to assess the consistency of the systemic importance implied by SRISK and MES, with traditional regulatory measures of systemic importance. All rank correlations between the estimated measures and a set of firm characteristics widely used as indicators of systemic importance are positive and statistically significant. Further tests also show that the estimated measures correctly adapt to prevailing market conditions. Lastly, evidence of causality between SRISK in the banking sector and the prime lending rate is presented. This result is consistent with previous literature that has shown that capital shortfalls may spill over into the real economy through lending activity.

Chapter 4

Misconduct Contagion and Crowding in the Stock Market: Evidence from South Africa

4.1 Introduction

In addition to impairing the trust between corporations and market participants, misconduct often has the effect of undermining efficiency in the capital markets; the recent wave of scandals that have repeatedly compromised the stability of South Africa's capital markets are testament to this. Incidents that stand out in particular, include the unceremonious dismissal of the Minister of Finance in December 2015, after which an already volatile currency depreciated to a record low against the US dollar, and the market capitalization of seventeen of the largest publicly traded financial firms fell by close $19 billion, a 16% loss in equity value. In another turn of events, Steinhoff International Holdings lost a record 62% of its market capitalization in a single day of trading in December 2017, after disclosing accounting irregularities in its financial statements. A sell-off ensued over the subsequent days, inducing a loss of more than 95% of the firm's value, and wiping out more than $20 billion of value in the equity market. Admittedly, incidents of this nature are not uncommon in the history of global financial markets.

Owing to the pervasiveness and significance of the repercussions, misconduct has not gone unnoticed in both public and academic discourse. Much effort has gone into developing an understanding of the consequences of scandals, for firms and the broader economy; available evidence indicates that share prices generally decline following the arrival of information that alleges misconduct (see Burns and Kedia, 2006; Gande and Lewis, 2009; Karpoff et al., 2008). Not only that, the consequences often extend beyond the trading environment of the implicated firms (see Fich and Shivdasani, 2007; Gleason et al., 2008). Other researchers have focused on the loss of reputation for implicated firms following allegations of misconduct (see Karpoff et al., 2008; Karpoff and Lott Jr, 1993). Moreover, it has been documented that malfeasance attracts higher country risk premiums in the bond market (Ciocchini et al., 2003); reduces household stock market participation (Giannetti and Wang, 2016); and lowers private investment, foreign direct investment and economic growth (see Brunetti et al., 1998; Mauro, 1995; Wei, 2000). Naturally, changes in perceived values or associated risks will elicit an immediate response from market participants looking to mitigate downside risks, by either hedging exposures, or liquidating positions. In the case of misconduct, it is easy to see how such behaviour may lead to risk concentrations, as congestion, otherwise known as crowding, occurs in the market.

In essence, there are two distinct streams of empirical research pertinent to the study presented in this chapter. The first documents how firm specific developments may, under certain circumstances, have material consequences beyond the firm's immediate environment. The second stream identifies the market clustering that occurs as a result of synchronicity in trading behaviours, as a potential amplifying channel for volatility spillovers, with significant implications for the measurement of systemic risk. This chapter addresses the two streams where they intersect. Specifically, four research questions are raised and examined hereinafter.

Using data from the South African equity market, the study addresses the question of whether allegations of misconduct exacerbate crowding for implicated firms. Under such circumstances, market clustering is expected to occur as a direct consequence of risk adjustments and the reversal of any share price inflation. Considering the previously documented evidence of information contagion following allegations of misconduct, it is reasonable to question whether crowding also changes significantly for the firms in a tainted firm's information network. The third research question is concerned with the consequences of malfeasance, for changes in the trading environment of a subset of firms with limited exposure to the domestic economic climate and currency volatility. Finally, the study interrogates the view that crowding not only increases exposure to systemic risk but also deteriorates liquidity.

Crowding, from an academic perspective, does not have a well established body of knowledge behind it, hence no canonical definition exists. Although, it is widely accepted that crowding occurs when market participants concentrate their positions on homogeneous risk factors or when they follow similar strategies resulting in crowded equity positions or crowded trades[1]. In simpler terms, participants act in the same way, at the same time, for the same reasons and this may lead to high correlations between both portfolio holdings and returns. To illustrate how this phenomenon may occur, consider the case of relatively sophisticated market participants that often use similar risk models, share similar trading strategies and even forced liquidation criteria. Not only that, such institutions typically face identical external requirements set by regulatory authorities, intended to safeguard the markets against various risks. A common shock is therefore likely to lead to synchronicity in trading behaviours, which may in turn destabilize the market. Fundamentally, crowding creates a coordination problem that results in greater exposure to various risks, including but not limited to contagion risk and liquidity risk.

The 'Quant Meltdown' of 2007, which led to several prominent hedge funds recording unprecedented losses, demonstrated clearly how crowding may, under certain circumstances, induce instability in the market[2]. At the time, several hedge funds made use of quantitative strategies that identified stocks using similar factors. When the factors fell out of favour, the exodus that followed exhausted liquidity in the market, resulting in larger losses than expected. Evidently, a better understand-

[1]Herding and crowded trades are related but not the same. Herding arises from deliberate decisions of agents follow each other's behaviour and therefore, could result in a crowded trade. However, a trade may become crowded for reasons other than the herding behaviour of agents

[2]See Khandani and Lo (2008)

ing of the dynamics of crowding and, the economic implications of market clustering, is essential for identifying the ways in which a financial system's resilience to excess price instability and volatility spillovers can be improved.

Collectively, the results reported here provide new insight into how misconduct influences trading behaviour, liquidity and systemic risk in the equity market. Essentially, the contributions of this paper are twofold: First, this study is among the first to examine crowding in the context of misconduct contagion. The available empirical literature has focused very little on how this phenomenon is affected by exogenous events. By examining changes in the trading and liquidity environments of linked firms, the study also builds on the literature that examines how information contagion in the public equity markets. Second, new evidence of the interrelationship between crowding, systemic risk and liquidity, contributes to the branch of literature that studies how market clusters may increase exposure to systemic risk and deteriorate market quality.

The remainder of this chapter is organised as follows. Related literature reviewed in Sections 4.2.1 and 4.2.2, and the research questions are expanded on in Section 4.2.3. Section 4.3 describes in detail, the data, the methodologies adopted to identify information networks and proposes a measure for the estimation of crowding. In Section 4.4 evidence of crowding following revelations of misconduct is presented. New evidence of the effects of crowding on systemic risk and liquidity is reported as well. Section 4.5 summarises the findings.

4.2 Related Literature and Hypothesis Development

4.2.1 Misconduct and Information Contagion

Generally, the available evidence indicates that share prices decline on the arrival of information that suggests the possibility of misconduct (Burns and Kedia, 2006; Dyck et al., 2013; Karpoff et al., 2008, 1999; Karpoff and Lott Jr, 1993). Dyck et al. (2013) and Karpoff et al. (2008) show that on average, between 22% and 38% of a firm's valuation is wiped out when allegations of corruption are brought to the attention of investors. Likewise, Burns and Kedia (2006) find evidence of an abnormal negative return of 8.8% for a sample of financial restatement announcements and Karpoff et al. (1999) document that press reports of misconduct related to the procurement of government contracts are accompanied by significant, and negative, abnormal returns for implicated firms. Arguments suggesting that the losses associated with misconduct are not only the result of the market adjusting to a more accurate representation of a firm's financial situation, but also reflect a loss of reputation have been presented in the literature. Karpoff et al. (2008; 1993) argue that the reputational cost is in fact large for firms accused or convicted of fraud and concluded that it amounts to 66%–90% of the loss in equity value. In addition to the effects on firm values, Murphy, Shrieves, and Tibbs (2009) documented that allegations of misconduct affect profitability and risk, by decreasing earnings and increasing risk.

Evidence can be found that demonstrates that misconduct has consequences for other publicly listed companies as well (Fich and Shivdasani, 2007; Gleason, Jenkins, and Johnson, 2008). Fich and Shivdasani (2007) found evidence of significant negative abnormal returns for companies that share directors with companies facing allegations of financial fraud. Similarly, Gleason et al. (2008) illustrated that accounting restatements with adverse effects on shareholder wealth, also prompt a decline in the value of non-restating firms in the same industry as the restating firm. These findings were later generalized by Scherbina and Schlusche (2018) when they showed that being at the centre of important company specific news developments that may have significance for other firms has an impact on return predictability. More recently, Bachmann, Ehrlich, Fan, Ruzic, and Leard (2019) documented a spillover effect following the 2015 Volkswagen (VW) emissions scandal, in the form of lower valuations and annual sales for non-VW German auto manufacturers. Zhang and Zhu (2021) also found that Chinese firms penalized for initial public offering (IPO) or merger and acquisition (M&A) fraud induce stock price declines among non-fraudulent firms sharing the same investment banks. The existence of such lead-lag effects, or return predictability, is not uncommon and has been documented extensively by several authors. Return predictability has often been attributed to differences in the degree of investor attention, as it is known that attention influences the speed at which information diffuses between companies (Bali, Peng, Shen, and Tang, 2013; Barber and Odean, 2007; Cohen and Frazzini, 2008; Hirshleifer, Lim, and Teoh, 2009; Lo and MacKinlay, 1990). In the process of interrogating the effects of misconduct by companies, researchers have remained cognisant of the fact that governments are responsible for shaping the environment in which financial markets operate. Therefore, misconduct by the state can also have adverse economic consequences.

One of the earliest studies to examine the impact of malfeasance on the real economy was by Mauro (1995); the author concluded that corruption, or the perception of it, is associated with a significant reduction in the ratio of investment to GDP. Similar evidence was reported in various studies that followed (see Brunetti, Kisunko, and Weder, 1998; Julio and Yook, 2012; Wei, 2000). Of particular interest, is the research that has addressed how politics influences real decisions in the financial markets through the channels of uncertainty and instability. In one study, Ciocchini, Durbin, and Ng (2003) demonstrated that, when issuing bonds, a higher risk premium is paid by countries that are perceived to be more corrupt. Boutchkova, Doshi, Durnev, and Molchanov (2012) contributed further by demonstrating that political risks affect return volatility and Pastor and Veronesi (2012) concluded that, increases in political risk are generally accompanied by lower share values and greater volatility and correlations. The relationship between exchange rates and political risk has been well documented too. Nearly all evidence indicates that greater political uncertainty is associated with increases in exchange rate volatility (see Almeida, Goodhart, and Payne, 1998; Andersen and Bollerslev, 1998; Bailey and Chung, 1995; Hlatshwayo and Saxegaard, 2016; Leblang and Bernhard, 2006). Maveé, Perrelli, and Schimmelpfennig (2016) also documented that, outside of international volatility shocks, one of the most significant drivers of exchange rate volatility in South Africa has been domestic political uncertainty.

4.2.2 Measuring Crowding and the Effects of Market Clustering

The question of how crowding should be measured has been addressed using various methods (Anton and Polk, 2014; Brown, Howard, and Lundblad, 2019; Bruno, Chincarini, and Ohara, 2018; Jia and Yang, 2017; Kinlaw, Kritzman, and Turkington, 2018; Menkveld, 2017a; Pojarliev and Levich, 2011; Stein, 2009; Yan, 2013; Yang and Zhou, 2016). Early on, Stein (2009), modelled crowdedness as the uncertainty about the number of traders in the market. Contributions that followed deviated from this view by making use of information on portfolio holdings and return correlations. For example, Anton and Polk (2014) and Bruno et al. (2018) measured crowding as the extent to which investors use portfolio construction techniques that would likely lead to overlapping portfolios. Whereas Brown et al. (2019) defined measures of crowding based upon collective hedge fund presence, Yan (2013) measured crowdedness as a function of short interest ratios and the exit rate of institutional investors. In contrast, Kinlaw et al. (2018), Menkveld (2017a) and Pojarliev and Levich (2011) identified crowding by analysing changes in the correlation structures of ex post returns. The simplest measures to date, based on trading volume data that makes a distinction between buyer and seller initiated trades, were proposed by Jia and Yang (2017) and Yang and Zhou (2016). Recognizing that crowding can cause or amplify financial distress, effort has gone into interrogating the effects of crowding on market quality as well.

The debate around the effects of crowding has focused on how this type of behaviour results in greater exposure to various risks including price instability, contagion risk and liquidity risk. Researchers have demonstrated that crowded trades have the effect of pushing asset prices away from fundamental values, and how these conditions are likely to persist in the absence of price based correction mechanisms to mediate the congestion (Barberis and Thaler, 2003; Hanson and Sunderam, 2014; Stein, 2009). Where market clusters exist in the presence of interconnected institutions, under certain conditions, seemingly unimportant events may be amplified into widespread market volatility. This assertion is supported by the work of Braun-Munzinger, Liu, and Turrell (2018); Cont and Wagalath (2016); Menkveld (2017a); Pojarliev and Levich (2011); van Kralingen, Garlaschelli, Scholtus, and van Lelyveld (2020) and Thurner et al. (2012). An investigation by van Kralingen et al. (2020) demonstrated that market clustering has a causal effect on the properties of the tails of stock return distributions. Similarly, Braun-Munzinger et al. (2018) found evidence indicating that the tail risk associated with large yield dislocations after shocks in the bond market, increases with the number of funds using passive investment strategies. When prices eventually start to correct, the losses realized by multiple highly correlated portfolio positions increase the risk of forced sales under unfavourable terms (i.e. fire sales), creating a cycle of further liquidations and price declines (Cont and Wagalath, 2016; Thurner et al., 2012). Pojarliev and Levich (2011) confirmed that crowded trades pose a significant risk once sentiment induces liquidation of positions by traders, and Menkveld (2017a) demonstrated how crowded trades pose a significant systemic risk to central clearing parties. In addition, available evidence indicates that crowding can increase the risks associated with price dislocation (Braun-Munzinger et al., 2018; Stein, 2009). The reason being that group behaviour can overwhelm the supply in the market when more capital is allocated to one trade opportunity relative to another.

4.2.3 Hypothesis Development

A plausible way in which crowding and misconduct can be linked[3] is as follows: when it is revealed to the public, news related to financial misconduct or corporate corruption is likely to change a firm's perceived value (see Cole et al., 2021). Assuming the efficient markets hypothesis holds, and investors make rational decisions based on available information, it is reasonable to conjecture that trade activity increases at the primary point of exposure, as the markets make the appropriate risk adjustments. This view is consistent with previous evidence of negative trading imbalances exhibited by institutional investors following the arrival of firm-specific news relating to the option backdating scandal of 2006âĂŞ2007 (see Bernile et al., 2015). The hypothesis that follows needs no further elaboration.

Hypothesis 4.1 *Crowding increases for firms directly implicated in allegations of misconduct.*

Following the arrival of negative news, it is not uncommon for market participants to employ strategies aimed at offsetting the risk of any adverse price movements or

[3]The terms "scandal" and "misconduct" are used broadly in referring to financial fraud, misrepresentation or malfeasance

mitigate downside risk by liquidating positions with common exposure. This view is supported by the empirical evidence of information spillovers for firms that are associated closely enough to have a collective reputation (see Bachmann et al., 2019; Scherbina and Schlusche, 2018; Zhang and Zhu, 2021). The impact of allegations of misconduct is therefore likely to extend beyond the primary point of exposure as information travels between interconnected firms, which gives the next hypothesis.

Hypothesis 4.2 *Crowding increases for firms in the information network of a firm tainted by allegations of misconduct*

Next, given that a government is responsible for shaping the environment in which a financial market operates, it is expected for political events with severe economic implications to have a significant effect on several macroeconomic variables, including currency volatility. Considering the risk-averse nature of market participants, the consequences of misconduct are likely to be reflected in the trading activity of firms with limited exposure to the domestic economic climate and currency volatility. Drawing on the econometric evidence of the volatility of the South African rand and domestic political uncertainty being intertwined (see Maveé et al., 2016), the following hypothesis is examined.

Hypothesis 4.3 *Crowding increases for rand-hedges following revelations of malfeasance.*

Several studies have found that more commonality in investments increases price dislocation and pay-off correlations, both of which have significant implications for the measurement of systemic risk (see Menkveld, 2017a; van Kralingen et al., 2020). The following hypothesis can be tested to provide further support for the view that crowding can increase the risks associated with price dislocation.

Hypothesis 4.4 *Crowding increases exposure to systemic risk and deteriorates liquidity.*

To conclude this section, the literature on misconduct and information flow has established that firm-specific developments are often reflected in a firm's information network. Furthermore, there is a consensus that crowding may increase the risks associated with common asset devaluation, which is a crucial default contagion channel relevant for the measurement of systemic risk. Having identified the main research questions in the section above, the next section describes the procedures and methods used to address the two streams of research where they intersect.

4.3 Data and Methodology

4.3.1 Sample Description

For this investigation, data on all JSE listed equities is collected from multiple sources. Intraday trade and quote data retrieved from the Market Quality Dashboard[4] is used to estimate trade directions, volatility and spreads. From Refinitiv

[4]The database provides trading data and key market quality metrics for select global markets. For more information see https://www.mqdashboard.com

Eikon, we obtain financial ratios, daily turnover values in local currency, stock ownership and analyst coverage information; Appendix B.1 describes these variables in further detail. Market capitalization and outstanding share values are provided by the JSE. In its entirety, the panel dataset spans seven years, starting in January 2014 through to March 2020. To avoid survivorship bias, the sample also includes all equity listings and de-listings over the sample period.

4.3.2 Rand-hedges

Rand-hedges, as they are colloquially known, are a subset of JSE listed firms that typically benefit from, or are unaffected by a weaker domestic currency, as they tend to have very limited exposure to South Africa by way of revenues or operations. Three broad categories of rand-hedges have been identified: (i) firms that are registered and operate abroad, (ii) firms with substantial foreign operations from which a considerable percentage of their profits are derived, and (iii) exporting firms that report results and pay dividends in hard currencies. Mining firms, for example, will price and sell their output in the open market in USD; therefore, any weakening of the South African rand would boost earnings that are converted back into the domestic currency for reporting profits/losses. A list of the firms considered in our analysis that meet these criteria is available in Appendix B.3.

4.3.3 News Counts

All news data is collected from Factiva[5]. For each firm, daily firm specific news headlines used to derive the news counts are retrieved from the start of 2015, through to the end of the sample period. A comprehensive count, however, may contain noise; therefore, filters are applied to the news items to produce additional counts that will unambiguously be understood to contain only material information. Altogether, the following alternative news counts are examined:

i All news: all news articles

ii Financial performance news: news relating indicators of a company's financial health and stability

iii Corporate action news: news relating to actions or events that bring material change to a company and affect its stakeholders, including shareholders and bondholders. This includes actions taken by a company itself or taken in relation to a company by other organizations

For each news type, only unique news items are considered, as the same news item may appear across multiple sources. The assumption is made that each news item is brought to the public's attention on the date on which it is timestamped, provided it is not a weekend or public holiday. If the item is dated on a weekend or public holiday, the news item is assigned to the next business day, assuming that this is when prices will reflect any relevant information.

[5] For more information see https://professional.dowjones.com/factiva/

4.3.4 Information Leadership

Following Scherbina and Schlusche (2018), information networks are identified using Granger causality regressions. Specifically, followers are those stocks whose log returns are Granger-caused by the log returns of their leaders. For each pair of stocks i and j, daily regression coefficients are estimated using a rolling window of 250 trading days, where the dependent variable is the daily log return of stock i and the independent variables are the daily lagged log returns of stock i, stock j and the market index:

$$r_t^i = b_0^{ij} + b_1^{ij} r_{t-1}^{mkt} + b_2^{ij} r_{t-1}^i + b_3^{ij} r_{t-1}^j + \epsilon^{ij}.$$

If the estimated coefficient $\hat{b}_3^{ij}$ is statistically significant, then stock j Granger-causes the return of stock i. In addition to identifying stable, long-term relationships, this methodology allows the identification of transitory (short-term) relationships, which would otherwise not identifiable through the traditional methods used in lead-lag literature. On any given day, the set of eligible followers is restricted to mid and high priced stocks[6] that traded on the previous trading day. The sample is restricted for the reason that these stocks are generally liquid and actively traded, and will therefore have sufficiently variable returns for statistical analysis.

[6] Greater than R15 per share

4.3.5 Crowding

Trading volume data is used to measure crowding. Specifically, the volumes of buyer and seller initiated trades inferred from intraday data using the Lee and Ready (1991) algorithm that classifies trades by their position relative to the prevailing best bid and ask prices[7]. The relative trade imbalance at time t, $RTI_{i,t}$, is equal to the difference between the buyer and seller initiated volume, divided by the number of shares outstanding:

$$RTI_{i,t} = \frac{BV_{i,t} - SV_{i,t}}{OS_{i,t}},$$

where $BV_{i,t}$ and $SV_{i,t}$ are respectively, the buyer- and seller-initiated volumes of stock i at time t, and $OS_{i,t}$ is the quantity of outstanding shares. Generally, $RTI_{i,t}$ is not equal to zero and positive (negative) value is indicative of a crowd on the buy (sell) side. As we are more concerned with changes in the intensity of crowding following a market event, than we are with changes in the direction of the crowd, the crowding index is defined as:

$$C_{i,t} = |RTI_{i,t}|.$$

Values closer to zero indicate minimal crowding on either side of the market, whereas relatively larger values indicate that a stock has undergone heavy buying/selling from investors.

[7] A trade is classified as seller (buyer) initiated on the condition that the execution price is closer to the prevailing best bid (ask) price. For trades that execute at the midpoint, the 'tick test' is used. In which case, the trade is classified as buyer (seller) initiated, if the price change immediately before the trade is positive (negative).

4.3.6 Research Design

Event study methodologies are used to examine changes in the trading environment surrounding eight instances of financial fraud, misrepresentation, corporate and political scandals (hereafter, collectively referred to as misconduct) that occurred between December 2015 and May 2019[8]. The change in crowding, $\Delta C_{i,t}$ at some time t relative to the event date, is defined as the natural logarithm of the ratio of $C_{i,t}$ divided the value of the crowding index, averaged across all trading days in the interval $t \in [-10, -1]$ (approximately two calendar weeks). Changes in volume traded, quoted spreads, intraday volatility and MES[9] are estimated in the same way.

Where misconduct occurs at the firm level, changes are evaluated for the implicated firms and their respective information networks, identified on the trading day immediately before the event date. In contrast, where malfeasance occurs and information leadership analysis is not feasible, changes are evaluated for the sample of rand-hedges.

In the next section, the principal findings of the study are reported. First, using the methodologies outlined above, an empirical analysis of information networks in the equity market is carried out. Then the relevant hypotheses are addressed in the order they are presented in Section 4.2.3.

[8]Each event is described in detail in Appendix B.2. For information that arrives outside of normal business hours, the event date becomes next trading day.

[9]Quoted spreads are calculated relative to the prevailing midpoint price i.e. $\frac{(\text{AskPrice}_{i,\tau} - \text{BidPrice}_{i,\tau})}{\text{MidPoint}_{i,\tau}}$. The daily quoted spread is calculated as time-weighted average defined by the duration that each quote was outstanding throughout the day. Intraday volatility is defined as the standard deviation of the log returns of the midpoint price sampled every five-minutes. Daily MES values are estimated using the methodology outlined in Section 3.3.2.

4.4 Results

4.4.1 Information Networks in the Equity Market

A summary of the Granger causality regressions used to identify information leaders and their followers is reported in Table 4.1. Panel **I** of the table presents this information after sorting firms into quintiles demarcated by the number of leaders and firm size. On average, firms with a relatively high number of leaders tend to be smaller than those with a lower number of leaders. This finding is expected and has previously been attributed to common market information being priced into large firms quicker than it is in smaller firms. Consistent with this view, the table also shows that large firms tend to have more followers than relatively smaller firms. The last column of the table reports the results of a test of the difference of means between the first and last quintiles; results indicate that the groups are significantly different from each other. That is, firms with more leaders are on average, significantly smaller than those with fewer leaders. Similarly, large firms have significantly more followers than smaller firms. Panel **II** of the table reports that 58% of the leaders are positive leaders (i.e. the estimated regression coefficient is greater than zero). Moreover, a pairwise comparison of leaders and their followers reveals that leader firms are generally older than the firms that follow them and that leaders are in the same industry as their followers only 22% of the time.

To examine the relationship between return predictability implied by the follower counts and news developments originating at the firm, a dataset consisting

Table 4.1. Descriptive statistics for leader and follower firms
Following the methodology described in Section 4.3.4, leaders are firms whose returns can be used to predict a follower's returns. The sample covers the period starting at the beginning of 2015. To avoid bias caused by overlapping estimation periods, only the last day of each year is considered in calculating the statistics. Panel **I** reports the statistics for all stocks eligible to be leaders/followers, in line with the definition in Section 4.3.4. Panel **II** only considers firms with at least one follower. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively

Panel I	Leader count quintiles					Difference
	1(Lowest)	2	3	4	5(Highest)	5-1
Avg. no of leaders	12.51	16.98	19.07	21.80	26.96	(t-statistic)
Market Capitalization (ZAR millions)	181 211,2	75 729,72	51 591,56	38 649,51	21 803,68	$-159\,407{,}52^{**}$ (-2.0068)
	Firm size quintiles					
	1(Smallest)	2	3	4	5(Largest)	
Market Capitalization (ZAR millions)	159.75	823.61	2 913,05	10 656,17	179 146,7	
Avg. no of followers	6.25	6.59	7.59	8.30	9.73	3.134^{***} (4.8205)

Panel II	
% of leaders that are +ve leaders	57.61
	% of sample
Leader older than follower	56.63
Leader same industry as follower	21.88

of daily news headlines and control variables often associated with sophisticated investor attention is used. Specifically, the following firm-specific characteristics are considered: Size, Volume, Momentum, Turnover, Price/Earnings ratio, Price/Book ratio, Analyst coverage and Institutional ownership%[10]. The news counts are defined in Section 4.3.3 and Appendix B.1 describes all the other variables in detail. The summary statistics for all the aforementioned variables are presented in Table 4.2.

Assuming that the observed number of news headlines increases when important developments occur at the firm, daily follower counts are regressed against the news variables and a combination of the remaining control variables. By definition, the response variable is non-negative, discrete and right skewed, therefore a Poisson

[10]Due to data availability, a smaller representative sample of fifty firms for which daily news headlines are available from the beginning of 2015 is used for this part of the analysis

Table 4.2. Descriptive statistics for investor attention variables.
This table presents summary statistics for the news variables and investor attention proxies. The news counts are defined in Section 4.3.3 and all other control variables are described in detail in Appendix B.1. The sample consists of fifty firms for which daily news headlines are available from January 2015.

Variable	Mean	St. Dev.	Lower Quartile	Median	Upper Quartile
All news	662.94	1253.22	48	147	585
Financial performance news	118.01	258.34	13	33	96
Corporate action news	182.03	391.31	13	44	138
Size$(\times 10^{12})$	0.1926	0.3584	0.0143	0.0488	0.2294
Volume$(\times 10^{6})$	2.1244	2.6556	0.3568	1.2121	2.8315
Turnover$(\times 10^{9})$	0.2591	0.4386	0.0212	0.1297	0.3331
Institutional ownership	0.6072	0.2116	0.5108	0.6359	0.7733
Momentum	0.1136	0.6563	-0.1253	0.0638	0.2404
Price/Book ratio	3.0120	2.6374	1.2584	1.9436	3.8228
Analyst coverage	8.4079	5.8665	3	9	13
Price/Earnings ratio	18.481	17.899	10.2394	14.745	21.351

fixed effects estimation is the appropriate procedure[11]. Any inference also assumes that investors can costlessly obtain and process all the relevant news information. Furthermore, all coefficients are estimated with cluster robust standard errors to account for the possibility of heteroskedasticity and/or autocorrelation. A summary of the estimated coefficients is provided in Table 4.3.

Statistically significant relationships between a firm's follower count and the proxies for sophisticated investor attention are revealed by the results presented in Panel **I** of Table 4.3. As can be seen, there is a positive relationship between the number of followers a leader has and its size, volume traded and analyst coverage across all model specifications. This finding is consistent with previous research that has

[11]Although a Poisson regression does not account for overdispersion (i.e. conditional variance is larger than the conditional mean) in the underlying data, like a negative binominal regression would, the latter does not control for unchanging covariates as it allows for individual specific variation in the dispersion parameter rather than in the conditional mean and therefore cannot be considered as a true fixed effects method.

Table 4.3. Multivariate analysis of follower counts.
This table presents the results of a multivariate analysis of follower counts. The sample of firms used is limited to a size of fifty firms for which daily news headlines are available from the beginning of 2015. For parsimony, Panel **II** reports only the coefficients of the alternative news counts where they are substituted into each of the five specifications shown in Panel **I**. Z-statistics are reported in parentheses. ***, ** and * indicate the 1%, 5%, and 10% significance levels, respectively

Panel I:	(1)	(2)	(3)	(4)	(5)
All news$(\times 10^{-4})$	-1.325** (-2.209)	-1.36** (-2.238)	-0.8879* (-1.671)	-0.8894 (-1.629)	-0.1151* (-1.83)
Size$(\times 10^{-12})$	0.7976** (2.493)	0.7750** (2.395)			0.9952*** (2.591)
Volume$(\times 10^{-6})$	0.1257*** (2.656)	0.1355*** (2.824)			0.1451*** (2.958)
Turnover$(\times 10^{-9})$			0.3074* (1.842)	0.3259* (1.889)	
Price/Earnings ratio		0.0022 (1.457)		0.0016 (1.004)	
Momentum	-0.1406*** (-2.879)	-0.1346*** (-2.839)	-0.1949*** (-2.917)	-0.1954*** (-2.821)	
Price/Book ratio	-0.02008 (-0.637)		-0.03192 (-1.106)		
Analyst coverage	0.03816** (2.279)	0.0401** (2.37)	0.03624** (2.382)	0.03867** (2.512)	0.03858** (2.261)
Institutional ownership	0.1311 (0.3615)	0.1340 (0.367)	0.1167 (0.3221)	0.1148 (0.3095)	
Panel II: Alternative news counts $(\times 10^{-4})$	(1)	(2)	(3)	(4)	(5)
Financial performance news	-2.298* (-1.786)	-2.239* (-1.824)	-1.844* (-1.718)	-1.723 (-1.554)	-1.334 (-0.960)
Corporate action news	-2.551** (-2.547)	-2.479** (-2.44)	-2.321** (-2.266)	-2.303** (-2.209)	-2.308** (-2.346)

shown that the level of investor attention influences the speed at which common market information is incorporated into share prices and therefore determines return predictability. Alternative specifications with turnover in place of size and volume produce similar results. In contrast, for momentum, there is evidence of negative and highly significant coefficients. Scherbina and Schlusche (2018) highlight that a negative momentum coefficient indicates that firms that have experienced low returns tend to have more followers, and further argue that this result conforms to the view that negative news travels slower across firms than good news. The results are however inconclusive in respect to growth and value stocks.

Growth stocks typically attract more attention from sophisticated investors, and for this reason, are expected to have more followers. Furthermore, it is well known that growth stocks tend to have high Price/Earnings ratio and Price/Book ratios. However, there is no evidence that either of these ratios has a significant influence on the size of a firm's information network. As expected, institutional ownership coefficients are positive in all specifications, however, none are statistically significant. Moving on to the relationship with firm specific news, it is apparent from Panel **I** of Table 4.3, that there is a negative relationship between the news and follower counts.

With the exception of specification (4), all news coefficients estimated in the baseline regressions are statistically significant and negative. Although these negative coefficients contradict the main findings of previous studies, it has also been documented that the relationship between news and follower counts is in fact, non-linear. In a study of Amex, Nasdaq and NYSE listed stocks, Scherbina and Schlusche (2018) demonstrated that only when news counts are squared, do the estimated coefficients become negative, suggesting that intensive firm specific news coverage/investor attention is associated with a reduction in the size of a firm's information network. In view of this explanation, there are factors to be considered in the context of the South African equity market, that could lend support to the observed negative estimates. Several authors have documented that relative to developed counterparts, emerging economies are more volatile[12], and that there is strong positive relationship between volatility and investor attention[13]. Therefore, it seems plausible that negative regression coefficients may be produced by relatively less intense news coverage, in comparison to previous findings. Turning back to the evidence in Table 4.3, it appears that greater news coverage attenuates return predictability as reflected by a

[12]see Aggarwal et al. (1999); Bekaert and Harvey (1997)

[13]see Andrei and Hasler (2015); Vlastakis and Markellos (2012)

decrease in the number of followers. An explanation for this might be that greater news coverage increases attention to a firm's information network as well, possibly due to the highly concentrated and interconnected equity market structures. Consequently, news diffuses faster into the information networks and brings about shorter delays in price reactions. Panel **II** of the table presents only the coefficients of alternative news variables substituted into each of the five specifications shown in Panel **I**.

As can be seen in Panel **II**, the results from the baseline regressions carry over into the analysis of the alternative news variables. Bar specifications (4) and (5) in the case of financial performance news, all coefficients estimated for the alternative news variables are reported to be negative and statistically significant. More importantly, the coefficients in Panel **II** are larger in magnitude in comparison to those presented in Panel **I**. This result is hardly surprising, given that the alternative variables consider only material information that is likely to impact prices in a meaningful way, whereas a comprehensive news count may include some noise. In unreported tests, criteria for eligible followers is adjusted to include illiquid stocks eliminated by the price threshold stipulated in Section 4.3.4. The tests produce consistent coefficients, suggesting that the results presented in Table 4.3 are robust to the changes.

In summary, material information that increases investor attention may be fully, or partially mirrored in a firm's information network. The aforementioned view is supported by evidence of an association between increased news coverage, and a decrease in the number of followers a firm has. The section that follows moves on to consider misconduct contagion.

4.4.2 Effects of Misconduct Contagion on Market Quality and Stability

Prior research has hypothesized and found evidence of significant negative abnormal returns for companies in a tainted firm's information network (see Fich and Shivdasani, 2007; Gleason et al., 2008). One can therefore reasonably assume that allegations of misconduct are associated with information contagion related to the reversal of share price inflation and risk adjustments. This section interrogates the hypotheses presented in Section 4.2.3, regarding the contagion effects of misconduct, by examining changes in intraday measures of market quality.

Information about misconduct and its consequences is typically conveyed to, and acted upon by market participants over multiple periods. To take this into account, the event study considers a narrow six trading-day window. Furthermore, for all measures, changes are estimated relative to their respective averages over the ten trading day interval prior to the event. Limiting the size of the event window helps to avoid contaminating any inference with the effects of unrelated material information that arrives prior, or subsequent to the event, in an environment where the arrival of such information is unpredictable. Appendix B.2 describes in detail all the misconduct events considered. The variables for which changes are estimated include, the crowding index defined in Section 4.3.5, volume traded, quoted spreads, intraday volatility and MES. Table 4.4 reports the estimated changes over the post-event period along with the results of univariate tests.

Table 4.4. Impact of misconduct –leaders and followers.
This table presents the average changes in crowding, volume traded, quoted spreads, intraday volatility and MES over the six trading days following the earliest date at which news of misconduct is reported. Five firm specific events are considered here; Steinhoff, EOH, Tongaat, MTN and Aspen. The VBS mutual bank scandal is excluded from this analysis as the banks has never been publicly listed, hence there is no way to identify followers using return predictability. Appendix B.2 describes in detail all the events considered. Changes are reported separately for the information leaders (five firms) and the informationally linked followers identified by Granger causality regressions (seventy-eight unique firms). For each variable, the change at time t is defined as the natural logarithm of the ratio of the value observed at time t, divided by the mean daily value of the variable, averaged across the ten trading days before the event date. The null hypothesis is that there is no change in the measures. t-statistics are reported in parentheses below the estimated changes. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively for a one sided t test

	Event window	ΔCrowding	ΔVolume	ΔQSpread	ΔIntraday	ΔMES
Leaders	$t = 0$	1.298^{**}	1.222^{**}	0.487^{*}	1.495^{*}	0.218
		(2.409)	(2.498)	(1.624)	(1.933)	(1.067)
	$t = +1$	1.558^{**}	1.173^{**}	0.273	0.750	0.811
		(2.170)	(2.544)	(0.791)	(1.347)	(1.257)
	$t = +2$	0.947^{*}	1.118^{**}	0.254	0.827	0.826
		(1.694)	(2.330)	(0.546)	(0.861)	(1.291)
	$t = +3$	0.683^{***}	0.685^{*}	0.248	0.605	0.837
		(4.063)	(1.960)	(0.661)	(1.229)	(1.327)
	$t = +4$	0.019	0.574^{*}	0.218	0.543	0.734
		(0.031)	(1.756)	(0.790)	(1.215)	(1.168)
	$t = +5$	-0.467^{*}	0.841^{**}	0.265	0.506	0.765
		(-1.745)	(2.183)	(0.858)	(1.451)	(1.313)
	$t = +6$	-0.360	0.313	0.139	0.554	0.736
		(-0.959)	(0.639)	(0.418)	(1.135)	(1.321)
Followers	$t = 0$	-0.302^{**}	0.021	-0.099^{***}	-0.055	0.026
		(-2.227)	(0.213)	(-2.447)	(-0.895)	(0.826)
	$t = +1$	-0.412^{***}	-0.139^{*}	0.034	0.116^{**}	0.084^{**}
		(-3.016)	(-1.313)	(0.683)	(1.770)	(2.143)
	$t = +2$	-0.596^{***}	-0.151	0.002	0.167^{**}	0.079^{**}
		(-3.472)	(-0.984)	(0.045)	(2.339)	(1.857)
	$t = +3$	-0.589^{***}	-0.318^{***}	0.103^{**}	0.034	0.065^{*}
		(-4.220)	(-3.056)	(1.830)	(0.460)	(1.538)
	$t = +4$	-0.547^{***}	-0.316^{***}	0.015	-0.022	0.064^{*}
		(-3.711)	(-2.529)	(0.289)	(-0.321)	(1.518)
	$t = +5$	-0.250^{*}	0.019	0.023	0.007	0.058^{*}
		(-1.599)	(0.194)	(0.448)	(0.126)	(1.315)
	$t = +6$	-0.740^{***}	-0.197^{*}	0.061	0.010	0.080^{**}
		(-3.919)	(-1.613)	(1.181)	(0.112)	(1.737)

Following the arrival of negative news, it is expected that either the reversal of any share price inflation attributable to incorrect information will occur, or the market will adjust a firm's value to more accurately represent its reputation or financial situation. For that reason, trade activity is likely to increase in the post-event period. For the implicated firms (i.e. information leaders), crowding is reported to increase on average, by 130% on the event date t_0. Positive changes in the crowding index are observed every day up until t_4 as well, however, only the changes between t_0 and t_3 are statistically significant. After t_5 crowding decreases relative to the pre-event values. The increases in crowding are accompanied by comparable changes in the volume traded. Observed changes in volume traded are at least equally statistically significant over the post-event period. Furthermore, the results show that, generally, both quoted spreads and intraday volatility increase following revelations of misconduct. However, statistically significant increases are observed only at t_0 for both variables. Likewise, MES increases on average by 22% to 84%, however, none of the changes are statistically significant. It is worth noting that, across all variables, the largest changes are generally observed between t_0 and t_2 and it appears that the size of the changes decreases with time.

Contrary to our expectations, crowding decreases on average, by 30% to 60%, between t_0 and t_3 for the tainted firms' information networks. Furthermore, Table 4.4 also shows that all subsequent changes in crowding are negative and statistically significant, with the largest decrease of 74% being reported at t_6. Volume traded is generally lower in the post-event period, however, this metric is reported to increase by 2% at t_0, albeit statistically insignificant. In addition, changes in quoted spreads

Table 4.5. Impact of misconduct –industry peers.
This table shows the event study results for the six trading days following the earliest date at which news of misconduct is reported. Full details are available in appendix B.2. Changes are reported for firms with the same two digit ICB sector code as the information leader (61 firms). The null hypothesis is that there is no change in the measures. t-statistics are reported in parentheses below the estimated changes. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively for a one sided t test

	Event window	ΔCrowding	ΔVolume	ΔQSpread	ΔIntraday	ΔMES
Industry peers	$t = 0$	-0.900^{***} (-3.699)	-0.573^{**} (-2.030)	-0.106^{*} (-1.422)	0.043 (0.340)	-0.034 (-0.590)
	$t = +1$	-0.597^{***} (-2.684)	-0.716^{***} (-2.964)	-0.096 (-1.184)	-0.151 (-1.280)	-0.034 (-0.368)
	$t = +2$	-0.458^{**} (-1.935)	-0.519^{**} (-1.872)	-0.073 (-1.142)	-0.163^{*} (-1.359)	0.007 (0.097)
	$t = +3$	-0.943^{***} (-3.026)	-0.886^{***} (-3.024)	-0.128^{*} (-1.615)	-0.214^{*} (-1.546)	0.012 (0.188)
	$t = +4$	-0.443^{**} (-2.173)	-0.603^{***} (-3.086)	-0.120^{**} (-1.849)	-0.268^{**} (-2.374)	0.031 (0.463)
	$t = +5$	-0.699^{***} (-2.538)	-0.728^{***} (-2.656)	-0.107^{*} (-1.538)	-0.370^{***} (-2.455)	0.018 (0.251)
	$t = +6$	-0.813^{***} (-3.173)	-0.544^{**} (-2.312)	-0.137^{**} (-1.747)	-0.284^{**} (-2.035)	0.011 (0.146)

and intraday volatility are generally positive for followers, consistent with the changes observed for the leaders. Although, both measures decrease at t_0. Just as well, MES increases by 3% to 8%, with the change observed at t_0 being the only observation not statistically significant.

Admittedly, using return predictability to identify informationally linked securities is not without its own concerns. It should be noted that this methodology identifies relationships only on the basis of statistical significance, and hence does not guarantee that the relationships are economically justifiable as well. A second point to note is that some statistically significant relationships may be transitory, such that they might not extend beyond the day on which they have been identified. For this reason, changes in the tainted firm's industry are also considered. Given that leaders are in the same industry as their followers only 22% of the time, as indicated in Table 4.1, a significant overlap between the followers and industry peers is unlikely. Table 4.5 reports the univariate tests for firms with the same two-digit ICB code as the firms facing allegations of misconduct.

Both crowding and volume traded decrease significantly for the industry peers in the post-event period, as shown by the evidence presented in Table 4.5. The measures are reported to decrease by 90% and 57% respectively, at t_0. Thereafter, crowding is on average, 44% to 94% less and volume 52% to 89% less. For both measures, all the observed changes are statically significant at at least the 5% critical level, and the largest changes are recorded simultaneously at t_3. The results show that quoted spreads generally improve for the industry peers, as indicated by the significant and negative change of 11% at t_0. The negative changes in quoted spreads persist through to t_6. Notwithstanding the positive change of 4% at t_0, intraday volatility decreases significantly as well. In comparison, MES generally increases in the post-event period, though none of these changes are statistically significant. In unreported results, additional tests are carried out to account for information leakages by adjusting the event window under investigation to include the two days prior to the event. The conclusions drawn from these results are consistent with those drawn from the information presented in Tables 4.4 and 4.5.

Recognizing that malfeasance often has economic consequences as well, Table 4.6 presents evidence on the effects of misconduct for the sample of rand-hedges. Although not statistically significant, crowding is reported to increase by 15% between t_0 and t_1. Thereafter, large negative and statistically significant changes are observed at t_2, t_3 and t_6 and the only significant increase is reported at t_4. In most cases, changes in volume traded occur in the same direction as the changes in crowding, however, these changes also differ in significance and magnitude. For example, volume increases significantly by 35% to 37% between t_0 and t_1. At the same time,

Table 4.6. Impact of misconduct –rand-hedge firms.
This table shows the event study results for the six trading days following the earliest date at which news of misconduct is reported. Full details are available in appendix B.2. Changes are reported for the subset of rand hedge firms. To ensure sufficient liquidity, only rand-hedges part the forty largest firms as measured by market capitalisation are considered; historically, this sub-sample is the most liquid market segment on the JSE. The null hypothesis is that there is no change in the measures. t-statistics are reported in parentheses below the estimated changes. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively for a one sided t test

	Event window	ΔCrowding	ΔVolume	ΔQSpread	ΔIntraday	ΔMES
Rand hedges	$t = 0$	0.145 (0.764)	0.368*** (3.430)	0.101*** (4.077)	0.224*** (4.136)	0.091** (2.243)
	$t = +1$	0.148 (0.737)	0.346*** (3.034)	0.287*** (3.840)	0.359*** (2.667)	0.060* (1.364)
	$t = +2$	−0.647*** (-2.662)	0.058 (0.569)	0.203*** (3.688)	0.128** (1.927)	0.096*** (2.739)
	$t = +3$	−0.500** (-2.168)	−0.209** (-1.830)	0.224*** (3.428)	0.130** (1.994)	0.060 (0.896)
	$t = +4$	0.422* (1.536)	0.278** (2.063)	0.062* (1.310)	0.193*** (2.498)	0.013 (0.246)
	$t = +5$	0.212 (1.196)	0.021 (0.237)	0.443*** (9.478)	0.370*** (4.469)	0.026 (0.622)
	$t = +6$	−0.437*** (-2.448)	−0.097 (-0.637)	0.247*** (7.430)	0.130** (1.787)	0.070** (2.005)

there is strong evidence of increases in both quoted spreads and intraday volatility.

Table 4.6 shows that, at t_0, the increases in quoted spreads and intraday volatility, of 10% and 22% respectively, are statistically significant at the 1% level. Following that, spreads increase by 6% to 44% and volatility by 13% to 37%. unsurprisingly, MES increases significantly by 6% to 10% between t_0 and t_3, and the positive changes persist in the days that follow.

Collectively, the information presented in Tables 4.4, 4.5 and 4.6 provides additional support for the idea of misconduct contagion. Interestingly, the evidence of increases in crowding for tainted firms is contrasted by equally significant evidence of decreases in crowding for the tainted firms' information networks. Evidence of coincidental changes in quoted spreads and MES over the post-event periods raises questions about the causal effects of crowding. The next section, therefore, moves on to investigate the interrelationship between crowding, exposure to systemic risk, and the liquidity environment.

Table 4.7. Descriptive statistics for crowding and volatility variables.
This table presents the summary statistics for the crowding index, volume traded and intraday volatility. The *Crowding* index is defined in Section 4.3.5. *Intraday volatility* is defined as the standard deviation of daily five-minute mid-quote log returns and *Volume* is total quantity of shares traded on a given day. The sample covers 416 firms at a daily frequency over the period starting in January 2015 till March 2020.

Variable	Mean	St. Dev.	Lower Quartile	Median	Upper Quartile
Crowding	0.03565	0.1379	0.00160	0.00985	0.03299
Intraday volatility	0.00441	0.013749	0.001245	0.00221	0.00397
Volume($\times 10^3$)	949.08	5515.29	5.95	108.76	716.64

4.4.3 Crowding as a Predictor of Systemic Risk and Liquidity

A growing body of literature has hypothesized that crowding is likely to increase exposure to adverse spillover effects, due to common asset devaluation. At the same time, a deterioration in liquidity is also expected, as congestion arises on one side of the market. If these theories hold, it is reasonable to expect crowding to contribute to increases in MES and quoted spreads. In this section, an assessment of the predictive power of the proposed crowding index is carried out using multivariate regression analysis. Table 4.7 presents the summary statistics of the variables considered.

Panel regression results for alternative specifications in which the number of independent variables are increased stepwise to include, *Crowding*, *Intraday volatility*, *Volume* and *Crowd direction*, a set of dummy variables used to identify the direction of the crowd, are reported in Table 4.8. Daily MES estimates are used as the dependent variable in specifications (1)–(3) and daily quoted spread values in specifications (4) and (5). A series of tests indicate that specifications with firm and time

Table 4.8. Multivariate analysis of the effects of crowding.
This table reports estimated coefficients and p-values of panel regressions with daily MES and quoted spread estimates as the dependent variables. Daily MES estimates are used as the dependent variable in specifications (1)–(3) and daily quoted spread values in specifications (4) and (5). The data consists of an unbalanced panel of 411 firms starting in January 2015 through to March 2020. All independent variables are lagged by a period of one trading day. The variable crowd direction is a categorical variable equal to zero for sell crowds ($RTI_{i,t} < 0$), one for buy crowds ($RTI_{i,t} > 0$) and two when there is no trade imbalance ($RTI_{i,t} = 0$). All panel regressions are estimated with firm and year fixed effects, and standard errors clustered at the firm level to account for the possibility of heteroskedasticity and/or autocorrelation. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dependant Variable				
Explanatory Variable ($\times 10^{-2}$)	MES			Quoted spread	
	(1)	(2)	(3)	(4)	(5)
Crowding	0.191*** (2.81)	0.171*** (2.66)	0.164*** (2.56)	0.799* (1.74)	0.792* (1.69)
Intraday volatility		6.117*** (4.66)	12.499*** (4.62)		
*log*Volume				−0.345*** (-5.15)	−0.229*** (-3.43)
Crowd direction:					
No crowd			0.101*** (4.20)		1.720* (1.82)
Buy crowd			0.002 (0.25)		1.369*** (2.67)
Intraday volatility interacted with:					
×No crowd			−11.606*** (-4.16)		
×Buy crowd			−4.692** (-2.13)		
*log*Volume interacted with:					
×No crowd					−0.024 (-0.24)
×Buy crowd					−0.099** (-2.31)
Time fixed-effects	Yes	Yes	Yes	Yes	Yes
Firm fixed-effects	Yes	Yes	Yes	Yes	Yes
Obs	280 335	278 758	278 758	269 083	269 083
N	411	411	411	416	416

fixed-effects are more efficient[14].

It is apparent from Table 4.8 that crowding is a significant driver of MES. Not only are all the crowding coefficients estimated in specifications (1)–(3) positive (0.164×10^{-2} to 0.191×10^{-2}), but they are statistically significant at the 1% level as well.

[14] A Breusch-Pagan test shows that it is necessary to include some type of fixed- or random- effects. For each regression specification, we also check the assumptions of the random-effects model with a Hausman test. The Hausman tests show that fixed-effects specifications are more efficient. A joint F test is used to see if time fixed-effects are needed. The null hypothesis that the coefficients for all years are jointly equal to zero is rejected, indicating that time fixed-effects are necessary.

In effect, a two standard deviation increase in the crowding index would increase MES by 4.5 –5.6 basis points[15]. Intraday volatility is reported to have a significant positive effect on MES in specification (2). This result is not surprising, as MES is estimated using time-varying conditional return volatilities. In specification (3), intraday volatility is allowed to have an asymmetric effect by including interaction effects with a categorical variable that indicates the direction of crowding. Adding interactive terms has implications for how the coefficient on intraday volatility is interpreted; coefficients of the interaction terms tell us how much of an effect the direction of the crowd has on the effect of intraday volatility on MES.

The coefficients estimated in the third regression indicate that conditional on a sell-crowd, intraday volatility has a statistically significant and positive effect on MES. More importantly, we find that the interactive effects have additional and significant explanatory power. When there is no crowding, volatility cannot be used to forecast MES. Although the estimated coefficient is positive, it is not statistically significant (0.892×10^{-2}, t-statistic=1.07). On the other hand, when there is a buy-crowd the estimated coefficient is positive and statistically significant at the 1%level (7.806×10^{-2}, t-statistic=3.88). The differences in the magnitude of the coefficients can be interpreted as evidence of volatility having an asymmetric effect on MES. Two conclusions can be drawn from this evidence. First, the significance of the effect volatility has on MES is conditional on crowding occurring, and second, the magnitude of said effect is larger for sell-crowds than it is for buy-crowds. Just as well, support for the view that crowding deteriorates liquidity is provided by the

[15] The standard deviation of the crowding index is 0.1379. Therefore $0.00045 = 2 \times 0.1379 \times 0.164 \times 10^{-2}$

information presented in Table 4.8.

Crowding coefficients in specifications (4) and (5) are almost equal in magnitude and significance. In both instances, a two standard deviation increase in the crowding index would increase quoted spreads by 22 basis points. Moreover, trade execution costs are known to improve as a consequence of increased trading activity. Accordingly, an increase in volume traded is expected to lead to a decrease in quoted spreads. As anticipated, the regression coefficient for volume traded, in specification (4), is negative and statistically significant at the 1% level. In specification (5), volume traded is allowed to have an asymmetric effect, similar to intraday volatility in specification (3).

Volume traded is reported to have a highly significant effect on quoted spreads, that is not conditional on crowding occurring. Table 4.8 shows that the effect of volume on quoted spreads when there is a sell crowd is statistically significant and negative(-0.229×10^{-2}, t-statistic$=-3.43$). The interactive effects between the crowd direction and volume are, however, not equally significant. An insignificant interactive effect when there is no crowding implies that the effect of volume traded on quoted spreads is not significantly different from when there is a sell-crowd (-0.253×10^{-2}, t-statistic$=-2.75$). On the other hand, when there is a buy-crowd, the effect of volume is significantly different from when there is a sell-crowd. To be precise, the decrease in quoted spreads associated with an increase in volume traded is larger in magnitude for buy-crowds (-0.329×10^{-2}, t-statistic$=-3.32$).

Valuable insights into misconduct contagion and externalities associated with crowding are presented in this section. An analysis of changes in intraday measures of market quality demonstrates how information contagion occurs following allegations of misconduct. The findings also provide some support for the conceptual premise that, the congestion and price dislocation associated with synchronous trading behaviour, will increase exposure to systemic risk while deteriorating liquidity as well.

4.5 Summary

An investigation of the interrelationships between misconduct, crowding and systemic risk, is carried out using a panel dataset of 411 firms over the seven years starting in 2014. For each firm, an information network of follower firms is identified using return predictability implied by Granger causality regressions, and it is shown that firm-specific developments have a significant and negative effect on the size of the networks. These results support the view that firm-specific developments, that significantly increase investor attention, may be fully or partially mirrored in a firm's information network. The aforementioned conjecture is then examined in the context of the crowding that occurs following allegations of corporate misconduct and malfeasance. Specifically, an event study of eight scandals that occurred between December 2015 and May 2019 provides evidence consistent with the hypothesis (H4.1) that crowding increases for firms facing allegations of misconduct. In contrast, for the tainted firms' information networks and industry peers, significant decreases in crowding are observed. Furthermore, there is limited evidence of statistically significant increases in crowding for rand-hedges after revelations of malfeasance. The results presented in this study also confirmed that crowding increases exposure to systemic risk and deteriorates liquidity. A series of panel regressions revealed that crowding is a significant predictor of MES and quoted spreads. One of the more interesting observations is that intraday volatility and volume traded have asymmetric effects on MES and quoted spreads, respectively, conditional on the direction of the imbalance between buyer and seller initiated trades.

Chapter 5

Cross listing in Emerging Markets and Market Quality: Evidence from the Johannesburg Stock Exchange

5.1 Introduction

Recent decades have seen significant institutional and structural changes in the financial sector, as global markets have gone through successive waves of consolidation and fragmentation. On one hand, harmonization of regulations has allowed large stock exchanges to expand regional presence and broaden their support for different asset classes. Developed markets, in particular, have been subject to increases in the level of integration either through mergers and acquisitions, or the use of joint trading systems. Noteworthy merger activities include the Euronext merger, and the Nasdaq-OMX merger[1]. At the same time, several public markets have also been characterised by the fragmentation of trading between stock exchanges and alternative trading venues in the form of Electronic Communication Networks (ECNs), Alternative Trading Systems (ATSs) and dark pools[2]. The changes in market structures, have been driven partly by advancements in communication technologies, and continue to be supported by regulatory reforms aiming to promote competition between different trading venues (OECD, 2016).

Despite the global trends described above, there is as yet, no indication of capital markets in developing economies having experienced similar successive waves of consolidation and fragmentation. Instead, the fragmentation of trading between multiple stock exchanges appears to persist in these markets. In China, for example, a unique stock market structure has since 1993, allowed firms to simultaneously list and trade, in Hong Kong and either one of the two mainland venues in Shanghai or Shenzhen. A regulatory change in 2007 allowed domestic Chinese investors to trade the Hong Kong-listed H-shares, previously only accessible to foreign investors, as well as the mainland A-shares, effectively creating a multi-market trading environment for 118 firms. Just as well, in India, it has become commonplace for firms to maintain listings

[1]Euronext was founded when the national exchanges in Amsterdam, Paris and Brussels merged in 2000. OMX owned and operated eight exchanges in the Nordic and Baltic regions before its merger with Nasdaq in 2007. For more information see https://www.reuters.com/article/us-factbox-exchanges-idUSTRE74F4RJ20110516

[2]ECNs and ATSs are non-exchange trading venues that automatically match buy and sell orders. For more information see https://www.sec.gov/rules/final/34-40760.txt. Dark pools are opaque crossing networks that allow trading on an anonymous basis. For more information see https://www.sec.gov/news/statement/shedding-light-on-dark-pools.html

on both the National Stock Exchange of India (NSE) and BSE (formerly Bombay Stock Exchange), the country's major stock exchanges. Since the NSE launched in 1994, over 1700 firms have cross-listed at BSE. The study presented in the sections that follow extends the literature concerned with this type of fragmentation.

In particular, an examination of the effects of recent regulatory developments in South African capital markets, presents new evidence on the implications of domestic cross-listings for market quality by addressing four research questions: (i) Does a new domestic cross-listing improve a firm's liquidity environment? (ii) Does the impact of a new domestic cross-listing on the liquidity environment differ significantly for high and low liquidity firms? (iii) Does market quality differ significantly across venues for firms with domestic cross-listings? and (iv) Does enhancing interoperability between stock exchanges improve the quality of the trading environment of cross-listed firms? In so doing, the study contributes to ongoing policy debates regarding inter-market competition and fairness in the multi-market trading environment created by a domestic cross-listing.

The developments in question stem from a series of amendments to the Financial Markets Act, legislated in 2014, to clamp down on unlicensed exchange infrastructures. As a result, in August 2016, the Financial Services Board (now the FSCA) issued a new stock exchange licence for the first time in almost six decades. Over the sixteen months that followed, three more licences were issued, bringing the country's total number of licensed exchanges to five. Interestingly, it appears that in recent years, there has been a renewed interest in improving the efficiency and fairness of capital markets in developing economies by promoting competition between domestic stock exchanges. For instance, new stock exchanges have emerged in Mexico and Myanmar[3] as well; interest continues to grow, as even authorities in Zimbabwe have expressed their desire for multiple local venues[4]. As intended, the proliferation of exchanges in South Africa has presented many firms with the opportunity to cross-list, thereby allowing their securities to trade at multiple domestic exchanges.

By cross-listing, firms create a multi-market trading environment for their securities, which in theory could either be detrimental to, or improve, liquidity due to the counteracting effects of splitting of order flow and increased inter-market competition. Notwithstanding the aforementioned, it is widely accepted that cross-listing is a value-enhancing decision. Furthermore, while firms often list their shares in more than one jurisdiction, doing so domestically is rare. Consequently, available literature on domestic cross-listings is dated and there is limited evidence of the effects of domestic cross-listings, outside of the impact on firm values (for a comprehensive review of the theories and empirical tests of cross-listing see Karolyi (1998, 2006)). Moreover, it appears that most contributions to the subject of domestic cross-listings have been restricted to studies of firms in the United States. One of the earliest investigations by Khan et al. (1993) documented that domestic cross-listings have a negative effect on equity returns. Subsequent contributions by Baker et al. (1994) and Khan et al. (1995) revealed significant differences in the abnormal returns observed for high and low liquidity firms, following a domestic cross-listing. In addition, Khan

[3]Mexico's second stock exchange, the Institutional Stock Exchange (BIVA) began operating in July 2018. The Yangon Stock Exchange, also the second stock exchange of Myanmar, opened its doors in December 2015.

[4]https://www.bloomberg.com/news/articles/2020-05-03/crisis-wracked-zimbabwe-plans-stock-exchange-in-victoria-falls

et al. (1995) concluded that a domestic cross-listing does not result in a significantly improved liquidity environment.

International cross-listings on the other hand, have been studied extensively. Although, efforts have also, for the most part, gone into investigating their effects in developed markets, including Britain, Canada, and Japan —few authors have examined the impact in emerging economies, with mixed findings at that (see Domowitz, Glen, and Madhavan, 1998; Hargis, 2000; Hargis and Ramanlal, 1998; Miller, 1999; Silva and Chávez, 2008). Levine and Schmukler (2006) documented a decrease in domestic turnover for emerging market firms that cross-list, or issue depositary receipts in foreign markets. In contrast, Berkman and Nguyen (2010) found weak evidence of an improvement in domestic liquidity for firms from emerging economies. Existing theories on the sources of the benefits of cross-listing, identified by the international evidence, include overcoming market segmentation arising from restrictions on ownership and capital flows, and reduction in information asymmetries as a result of increased visibility and investor awareness. In the case of a domestic cross-listing, it is clear how these hypotheses become inconsequential. Whether the absence of the benefits often used to rationalize international cross-listings could elicit a different reaction from the market in a domestic setting, remains an open empirical question. Furthermore, the literature is as yet to provide evidence on the impact of domestic cross-listings on market quality in emerging economies.

This study is among the first to examine the impact of domestic cross-listings using intraday measures of trade activity and liquidity, as previous related research considered only volume-based measures (see Baker et al., 1994; Khan et al., 1995, 1993). Moreover, the circumstances under which fragmentation is taking place in the South African equity market, provide a framework for a unique natural experiment. In particular, contributions are made to the ongoing dialogue concerned with, whether cross-listing is in and of itself a value-enhancing decision, or if the associated benefits exist only in the presence of information and microstructure asymmetries typically associated with cross-listings in different jurisdictions. Further clarification of the research questions is provided in Section 5.2.2, along with the testable hypotheses.

The study is organised in the following way. Section 5.3.1 expands on the details of the sample used in the analysis. Sections 5.3.2 and 5.3.3 outline the market quality measures and the research design. Section 5.4 reports event study results suggesting that there is no significant improvement in market quality after cross-listing. Evidence of market dominance by the JSE and improved market quality being conditional on enhanced interoperability between venues is presented as well. Section 5.5 summarises the findings.

5.2 Related Literature and Hypothesis Development

5.2.1 The Effects of Cross Listing on Market Quality

Generally accepted explanations as to why cross-listing is a value-enhancing decision, have to do with overcoming market segmentation, improved information disclosure and improved quality of the trading environment. The relevance of the segmentation hypothesis stems from the belief that international cross-listings can overcome barriers to international investments; including restrictions on capital flows and foreign ownership or simply not knowing about a security (see Merton, 1987; Stapleton and Subrahmanyam, 1977). By providing an alternative trading venue, firms are able to broaden the shareholder base and induce participation by investors who otherwise would not trade. Greater participation leads to greater risk-sharing, which in turn reduces the firm's cost of capital, as the risk premium compensating for the investment barriers becomes irrelevant (Alexander, Eun, and Janakiramanan, 1988; Doukas and Switzer, 2000; Foerster and Karolyi, 1999; Miller, 1999). Errunza and Miller (2000) studied one hundred and twenty-six firms from thirty-two countries, and reported evidence of a 42% decline in the cost of capital after the firms cross-listed. Likewise, Lins, Strickland, and Zenner (2005) provided evidence of an improvement in access to capital after cross-listing in the United States, for a sample of firms from emerging markets. Additional evidence was later provided by Hail and Leuz's (2009) investigation of firms with cross-listings on exchanges in the United States; the study found that the cost of capital decreased by 70 to 120 basis points after cross-listing. Evidently, the market segmentation hypothesis has provided valuable insight into why cross-listing is a value-enhancing decision. However, this theory is waning in significance, as firms continue to cross-list even as global capital markets become more integrated and the investment barriers dissipate. On account of the changing global market structures, the recent debates have paid more attention to hypotheses regarding information disclosure and the quality of the trading environment.

Early on, Fuerst (1998) argued that the decision to cross-list may be used by some firms as a signalling mechanism. Specifically, a cross-listing on a larger exchange with stricter disclosure requirements and shareholders' protection rights, may be seen as a signal by management, to the market, about the firm's outlook for the future. Under such circumstances, the reduction in information asymmetries would be further reinforced by increased attention from sophisticated investors; in a study of firms that cross-listed in New York and London, Baker, Nofsinger, and Weaver (2002) showed that cross-listing in these markets generally increases the firm's analyst and media coverage. As can be expected, an increase in analyst coverage often has an impact on estimates of future financial outcomes. Lang, Lins, and Miller (2003) found that firms that cross-list on exchanges in the United States have greater earnings forecast accuracy, relative to firms that do not cross-list. Corresponding evidence was presented in subsequent studies that demonstrated that firms that cross-list in relatively larger markets tend to benefit from increased company visibility (Bailey, Karolyi, and Salva, 2006; Fernandes and Ferreira, 2008). By committing to a higher level of disclosure and scrutiny, a firm improves its information environment and reduces the asymmetry of information, a change associated with higher market valuations.

Prior research has confirmed that cross-listings are associated with positive stock market reactions. By using event study tests, researchers have shown the existence of significantly positive abnormal returns subsequent to a firm announcing its intention to cross-list (see Amira and Muzere, 2011; Doidge, Karolyi, and Stulz, 2004; Doukas and Switzer, 2000; Foerster and Karolyi, 1998, 1999; Miller, 1999; Roosenboom and Van Dijk, 2009; Smith and Sofianos, 1997). Studies of firms that cross-listed in the United States found evidence of a 40% to 50% increase in the combined volume and value of shares traded, compared to that in only the home market before the cross-listing (Foerster and Karolyi, 1998; Smith and Sofianos, 1997). Likewise, Roosenboom and Van Dijk (2009) showed that the announcement of a cross-listing in a foreign market leads to a 0.98% increase in a firm's market valuation. Doidge et al. (2004) demonstrated that after cross-listing in the United States, a cross-listing premium arises, owing to the fact that the growth opportunities of firms that cross-list are considered more valuable than those of firms that do not. A major limitation of the contributions made to date is the almost exclusive focus on —United States firms cross-listing abroad, emerging market firms cross-listing in the United States and United States firms cross-listing on other local exchanges. This bias towards international evidence is also present in the investigations that have addressed changes in the liquidity environment.

Ample evidence in the literature details how international cross-listings might enhance the domestic liquidity of firms (Berkman and Nguyen, 2010; Fanto and Karmel, 1997; Foerster and Karolyi, 1998; Frijns, Gilbert, and Tourani-Rad, 2010; Mittoo, 1992; Visaltanachoti and Yang, 2010). International evidence potentially relevant in the study of domestic cross-listings, includes an investigation by Domowitz, Glen, and Madhavan (1998), whose findings suggest that an improvement in domestic liquidity due to increased inter-market competition, is conditional on transparency between the markets. Hargis and Ramanlal (1998) provide evidence of the role played by information transparency in the extent to which cross-listing has a positive impact on domestic market liquidity and the volume traded. While the widely accepted view is that cross-listing improves liquidity, there is still extensive ongoing debate about how appropriate this generalization is.

Some studies have also produced evidence suggesting that the benefits associated with cross-listings vary with firm characteristics such as size and country of origin (Bahlous, 2013; Berkman and Nguyen, 2010; Lins, Strickland, and Zenner, 2005; Noronha, Sarin, and Saudagaran, 1996; Roosenboom and Van Dijk, 2009; Silva and Chávez, 2008). Although Berkman and Nguyen (2010) found a significant improvement in liquidity after cross-listing, after taking into account the contemporaneous changes in liquidity of firms that do not cross-list, there is no evidence of a significant improvement in domestic liquidity. Moreover, Bahlous (2013) and Roosenboom and Van Dijk (2009) demonstrated how the impact of cross-listing varies with the destination market. In particular, they showed that the highest valuation gains occur after cross-listing in the United States, followed by London and then other European markets. These findings suggest that cross-listing in more developed capital markets has greater associated benefits. Furthermore, available evidence indicates that emerging market firms benefit more from cross-listing, in comparison to firms from developed markets (Lins et al., 2005). Some researchers have also argued that the direction of changes in market quality after cross-listing will depend on the level of information asymmetry between the listing markets (Domowitz, Glen, and Madhavan, 1998; Halling, Pagano, Randl, and Zechner, 2008). These mixed findings have motivated several authors to explicitly question why some firms do not benefit from cross-listings.

An important way in which cross-listings have been hypothesized to be detrimental to liquidity and market quality in general, is through the diversion of order flow to alternative trading venues (Chowdhry and Nanda, 1991; Lang, Lins, and Miller, 2003; Levine and Schmukler, 2006). The negative effects of order flow migration were demonstrated by Levine and Schmukler (2006), in a study of 2900 firms from emerging markets that cross-listed in foreign public markets. Their evidence indicates that domestic turnover decreases, on overage, by 10% after cross-listing. Naturally, order flow migration is a cause for concern particularly for smaller venues that, as a direct consequence of a cross-listing, often face competition from well established, highly liquid and deeper trading venues with lower information and transaction costs (Chowdhry and Nanda, 1991; Lang et al., 2003). However, the negative effects of order flow migration have also been found by Hargis and Ramanlal (1998) to be less pronounced in markets where there are restrictions on foreign ownership. Effort has also gone into understanding the dynamics of the multi-market environment created by cross-listings.

The literature has documented that the volume and volatility of cross-listed stocks are, on average, higher when the home markets are open (Howe and Ragan, 2002; Menkveld, 2008). These findings are consistent with Hagerty's (1991) prediction that market quality improves when the number of substitute assets in a market is increased, as this limits the ability of liquidity providers to set wide spreads. Moulton and Wei (2009) also presented strong evidence of lower spreads and more quoted depth for cross-listed stocks when trading hours at the listing venues overlap, relative to when they do not. Likewise, Menkveld (2008) illustrated how traders benefit may from splitting order flow across venues and found evidence of greater volatility, volume and liquidity during overlapping trading hours for a sample of British and Dutch firms with NYSE listed ADRs.

5.2.2 Hypothesis Development

Four research questions are identified where contributions can be made to the cross-listing literature.

First, the study addresses the question of whether market quality improves on the JSE, for a sample of JSE listed firms that cross-list at A2X. What is not yet clear, is how the effects of competition, fragmentation and the incentives to cross-list offset one another in a domestic setting. In general, the impact that cross-listing has on market quality is uncertain because of the two opposing effects of competition and fragmentation. Be that as it may, previous research has also shown that there are benefits to cross-listing in a stricter regulatory environment or a more developed market. In the South African domestic setting, not only do the exchanges operate in identical regulatory environments, but relative to the JSE, A2X is a significantly smaller market. In effect, a firm that cross-lists at A2X does not stand to benefit from the greater shareholder base, visibility, and liquidity associated with a more developed market. Neither does its information environment become more transparent, as it is not subject to further regulatory scrutiny. Hence, it could conceivably be hypothesised that a domestic cross-listing under these conditions is unlikely to be beneficial for the firm.

Hypothesis 5.1 *Market quality does not improve at the JSE after cross-listing on A2X.*

Under improved market quality conditions, greater trade volumes, and lower spreads, volatility and quote to trade ratios are expected. The second question contemplates whether the impact of a domestic cross-listing varies with a firm's pre-cross listing liquidity characteristics, as researchers have demonstrated that abnormal returns from cross-listing differ significantly for high and low liquidity firms (Baker et al., 1994; Khan et al., 1995). With that in mind, the following hypothesis is tested.

Hypothesis 5.2 *The effects of a cross-listing on market quality at JSE are related to the firm's pre-cross listing liquidity characteristics.*

The third question contributes to the debate around the significance of observed differences in market quality at the home and cross-listing destination venues. Pagano's (1989) two-period model identifies an equilibrium in which both markets in a multi-market setting can survive, but only under a specific set of assumptions—including equal transactions costs and equal numbers of traders in each market. The unrealistic nature of these assumptions suggests that one market will dominate. Furthermore, Chowdhry and Nanda (1991) predicted that, in a multi-market trading environment, informed and large liquidity traders will gravitate toward a single market. Not only that, but the dominant market is hypothesized to be the one with the lowest trading costs; previous cross-listing literature has suggested that this is typically the home market (Frijns et al., 2010; Halling et al., 2008).

Hypothesis 5.3 *In the post-cross listing multi-market environment, the JSE will be the dominant market.*

Lastly, the study calls into question whether the absence of market infrastructure and legislation to mitigate information asymmetries between venues has a bearing on market quality in the multi-market environment for domestic cross-listings. International cross-listing literature has documented that information asymmetries have a significant influence on the benefits associated with cross-listings. In particular, it has been argued that where inter-market information linkages are poor, market quality is unlikely to improve. The disjoint structure of the South African equity market provides an opportunity to ascertain whether previous findings of the significance of inter-market transparency in international cross-listing outcomes may be generalized to include domestic cross-listings as well.

Hypothesis 5.4 *Improvement in market quality after a domestic cross-listing is conditional on interoperability between venues.*

In summary, relatively little is known about domestic cross-listings. Furthermore, owing to a bias towards evidence from developed markets, what remains unclear are the implications of such microstructure changes for market quality in emerging economies. Gaps in the literature where contributions can be made have been identified and discussed in this section. In Section 5.3, the research design and methodologies used to address the open empirical questions are laid out.

5.3 Data and Methodology

5.3.1 Sample Construction

At the end of April 2020, according to a list provided by the exchange, there were 121 dual- and cross-listed securities[5] trading at the JSE. After excluding all securities not cross-listed on A2X, thirty-six securities remained, from which the following were eliminated as well: five exchange-traded products; one firm that cross-listed on a foreign exchange within the twelve-month window prior to listing on A2X; two firms with less than two months JSE data prior to listing on A2X; and two preferred stocks.

Each of the remaining twenty-six securities was then paired with all JSE listed securities that are (i) not cross-listed, and (ii) have the same ICB industry code. Using one-to-one matching without replacement[6], the best match was identified by

[5] Including both inward and outward listings, which are either primary or secondary listings on their respective exchanges.

[6] If stock X is matched with stock Y, then X is disregarded as a potential match for all subsequent cross-listings

computing a matching score for each pair, similar to Huang and Stoll (1996), and selecting the match that minimizes this score. The score is defined as the sum of squared relative differences, in average market capitalization and average daily volume traded, over the two months before the cross-listing announcement.

$$Score_{match} = \sum_{j=1}^{2} \left(\frac{X_j^{cross} - X_j^{match}}{\left(X_j^{cross} - X_j^{match}\right)/2} \right)^2 , \tag{5.1}$$

where X_j is either one of the matching characteristics. The superscript *cross* denotes a cross-listed stock, while the superscript *match* denotes the matched stock. To clarify, the best match is defined as the firm closest to the cross-listed firm, with respect to size and volume traded. On all announcement dates, the sample of eligible matches included all non-cross-listed stocks that later de-listed, in order to avoid survivorship bias. Announcement and listing dates were obtained from market notices published by the JSE's Stock Exchange News Service (SENS).

5.3.2 Market Quality Measures

All market quality measures are calculated at a daily frequency using intraday trade and quote data. Changes in trading activity are evaluated with respect to volume traded, average trade sizes and the quote to trade ratio. The quote to trade ratio is a ratio of the number of quote updates to the number of executed trades, where a quote update is any change in the best bid or best ask prices, or the order size at these prices. This metric is often used as a proxy for measuring the efficiency of quotes in distributing information. Quoted and effective spreads[7], and intraday volatilities are used as measures of liquidity and transaction costs.

Quoted spreads measure the indicative cost of immediately executing a small round-trip trade at the best available prices. The quoted spread for security i at some time τ during a given trading day is equivalent to

$$\mathrm{QuoSpr}_{i,\tau} = \frac{(\mathrm{Ask}_{i,\tau} - \mathrm{Bid}_{i,\tau})}{\mathrm{MidPoint}_{i,\tau}} \times 100. \tag{5.2}$$

$\mathrm{Ask}_{i,\tau}$ and $\mathrm{Bid}_{i,\tau}$ are the best ask and bid prices respectively, and $\mathrm{MidPoint}_{i,\tau}$ is the midpoint price $\left(\frac{(\mathrm{Ask}_{i,\tau}+\mathrm{Bid}_{i,\tau})}{2}\right)$. Daily quoted spreads are a time-weighted average of $\mathrm{QuoSpr}_{i,\tau}$ i.e. each quote is weighted by the duration that it was outstanding (prevailing) during the trading day. Effective spreads, on the other hand, measure the actual cost of immediately executing a small round-trip trade, keeping in mind that trades can execute at prices inside the bid-ask spread.

$$\mathrm{EffSpr}_{i,\tau} = 2\mathrm{D}_{i,\tau} \times \frac{(\mathrm{P}_{i,\tau} - \mathrm{MidPoint}_{i,\tau})}{\mathrm{MidPoint}_{i,\tau}} \times 100. \tag{5.3}$$

$\mathrm{P}_{i,\tau}$ is the trade execution price for security i at time τ. $\mathrm{D}_{i,\tau}$ indicates the direction of the trade; equal to one for buyer initiated trades and negative one for seller initiated trades. Trade directions are inferred from the data using the Lee and Ready (1991) algorithm. Daily effective spreads are a value-weighted average of $\mathrm{EffSpr}_{i,\tau}$ i.e. the effective spread for each trade executed during continuous trading sessions, is weighted by the value of that trade. For the estimation of intraday volatility, on

[7] Percentage (relative) spreads are used in order to control for stock price differences.

any given day, the measure is defined as the standard deviation of the log-returns of the midpoint price sampled every five minutes.

The sample of cross-listed firms is further divided into two liquidity groups identified using Amihud (2002) ratios; defined as the absolute stock return divided by the value traded. In essence, the ratio is a measure of the price impact of order flow, or the absolute price change associated with one rand of trading volume.

$$ILLIQ_{i,t} = \frac{\mid r_{i,t} \mid}{\mathrm{ZARV}_{i,t}} \times 10^6. \tag{5.4}$$

$\mathrm{ZARV}_{i,t}$ and $r_{i,t}$ are the rand volume traded and percentage log return, respectively, for security i at time t. The ratio is multiplied by 10^6, so that $ILLIQ_{i,t}$ becomes the absolute price change per one million rand of trading volume. A low value indicates that it is possible to trade large quantities of the security with minimal price impact in response to the order flow. Liquid securities will therefore have lower ratios.

5.3.3 Methodology

In an assessment of the effects of a cross-listing, there are two justifiable event dates worth considering. The first is the date on which the cross-listing is announced, and the second is the effective date on which trading commences at the destination venue. If the efficient market hypothesis holds, all available information is reflected in asset prices. Accordingly, the appropriate event date would be the announcement date, as transaction costs can reasonably be expected to adjust on that day. However, the diversion of order flow only occurs once trading commences at the destination venue; hence the cross-listing date is of some significance as well, since the costs associated with fragmentation can only be observed from that day. For the sake of prudence, both event dates are contemplated in the analysis. Consideration is also given to a sub-sample of twenty securities for which the time between the cross-listing announcement and effective trading dates is exactly one calendar week. From this sub-sample, inference can be made about whether there is a difference in the market's response to the announcement and the actual cross-listing.

The change for security i over some interval t, relative to the event date, $\Delta metric_{it}$, is equivalent to the natural logarithm of the daily metric values averaged over t, divided by a pre-event average. Specifically, the change is a ratio of the average metric value in week (month) t, to the average metric value over the week (month) before the event date. Pairwise differences, or adjusted changes, are also estimated in order to control for contemporaneous market quality changes of firms that do not cross-list. A cross-listed firm's adjusted change is equal to the difference between its unadjusted change, and the unadjusted change of its matched non-cross-listed firm. Univariate tests of the significance of the unadjusted changes are carried out. In the same way, tests are carried out on adjusted changes to determine whether unadjusted changes of cross-listed firms are significantly different from those of firms that do not cross-list. Another issue addressed in this study is the difference in market quality at the listing venues of cross-listed stocks. After pairing each firm's securities across the venues, a univariate matched-sample comparison is used to assess the distribution of trading between venues and evaluate differences in the cost of liquidity.

The various methods employed in our assessment of the impact of domestic cross-listings have been outlined in this section. In particular, high-frequency intraday measures of market quality are used to assess changes in the trading environment following a domestic cross-listing. Empirical results obtained using the described analytical procedures are reported in Section 5.4.

5.4 Results

5.4.1 Matching Firms

Descriptive statistics for the cross-listed firms and the sample of matched firms are presented in Table 5.1. For each matched pair, the daily metric values are estimated and averaged over all trading days in the two months before the respective cross-listing announcement dates. Matched pair differences are reported in the last column of the table. On average, matching firms are reported to have higher trade volumes, lower spreads, and lower volatility, when compared to the cross-listed firms. However, there are no significant differences between the groups, as indicated by the p-values reported in the parenthesis. In short, the results indicate that the matching methodology is effective.

Table 5.1. Descriptive statistics for cross-listed and matched sample firms.
This table reports descriptive statistics for the cross-listed firm, the matching firms and the mean of the differences of the twenty-six matched pairs. The sample period covers the years 2017–2020. Matches are identified on the respective cross-listing announcement dates and all variables are averaged over the two calendar months prior to this event date. P-values of a two sided t-test of the mean of the differences between the cross-listed and matching firms are reported in parentheses below each estimate. Activity measures are volume, average trade sizes and quote to trade ratio. Liquidity and transaction cost measures are the Amihud ratio, relative spreads and intraday volatility. ***, ** and * indicate statistical significance at the 1% , 5% and 10% levels, respectively

	Cross listed				Matches				Difference (a) - (b)
	Min	Max	Median	Mean (a)	Min	Max	Median	Mean (b)	
Trade volume $\times 10^3$	24	9 738	639	1 445	11	11 932	828	1 653	-208 (0.45)
Avg trade size	82	50 794	1 421	5 231	154	22 467	1 231	3 916	1 314 (0.49)
Quote to trade ratio	2.73	40.91	7.26	9.24	2.27	28.79	7.20	9.33	-0.09 (0.95)
Amihud ratio	0.0007	2684	0.093	117.45	0.002	1255	0.082	93.91	24.13 (0.73)
Quoted spread (bps)	7.36	3 686	30	305.82	8.98	1 264	36.87	172.59	133.23 (0.28)
Effective spread (bps)	5.99	4 056	19.87	314.76	6.96	1 006	25.87	148.02	166.73 (0.27)
Intraday volatility ($\times 10^{-3}$)	1.44	24.5	2.34	3.9	1.25	9.21	2.29	2.98	0.928 (0.37)

5.4.2 The Effects of a Domestic Cross Listing on Market Quality at the Primary Venue

The implications of a cross-listing for market quality are generally uncertain because of the two opposing forces of inter-market competition and fragmentation. On one hand, increased inter-market competition may place downward pressure on the cost of trading across venues. On the other hand, fragmentation has the potential to deteriorate liquidity when order flow is diverted to alternative venues, and the share of trades executed at the primary venue declines. How these effects counteract one another is therefore an empirical issue. Table 5.2 presents evidence on the changes in market quality on the JSE for firms that cross-list on A2X.

Weekly average changes in market quality are reported in Panel **I** of Table 5.2. The results presented in the table reveal that trade volume declines significantly, by

42%, in the first week after a cross-listing is announced. However, none of the other metrics are found to have changed significantly over that same period. In the second week after the announcements, once trading commences on A2X, only the quote to trade ratio is reported to change significantly. The ratio declines by 16%. The results also show that spreads increase in most of the six weeks following the announcement, and intraday volatility decreases in every week. Although, none of the changes in these metrics are statistically significant. Controlling for the contemporaneous changes of matched firms that do not cross-list yields similar results.

The adjusted metric changes are reported in the last four columns in Panel **I** of Table 5.2. A positive value implies that the metric value increases (decreases) more (less) for the cross-listed firms. The table shows that, in general, the market quality of firms that cross-list does not improve significantly, relative to the non-cross-listed firms. In fact, in most weeks there is a relative decline in the volume traded of the cross-listed firms, with significant differences reported only in the third and sixth weeks. Positive adjusted changes in spreads, although not statistically significant, indicate a relative increase in transaction costs for the cross-listed firms. The only other statistically significant adjusted change observed is in the effective to quoted spread ratio in the second week. This ratio is for all intents and purposes, a measure of price improvement i.e. the execution of trade at a price better than the prevailing quote. The positive differences imply that there is a relative decline in cost savings for the cross-listed firms once trading commences at the alternative venue. Everything considered, the information presented in Panel **I** of Table 5.2 suggests that changes in the trading environment when a firm announces a cross-listing are

Panel I

	Cross listed						Adjusted (Cross listed − Matching)					
	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6
Trade Activity												
ΔTotal trade volume	-0.421*	-0.312	-0.090	0.084	0.322	-0.008	-0.443	-0.225	-0.348*	-0.208	0.119	-0.216*
	(-1.46)	(-0.83)	(-0.83)	(0.36)	(1.08)	(-0.04)						
ΔAvg trade size	-0.285	-0.151	0.096	0.087	0.151	0.047	-0.276	0.032	0.014	-0.205	0.073	-0.052
	(-1.19)	(-0.53)	(0.59)	(0.42)	(0.92)	(0.37)						
ΔQuote-to-trade ratio	-0.032	-0.162*	-0.100	-0.064	-0.163*	-0.221*	-0.068	0.015	0.050	-0.073	-0.118	-0.114
	(-0.37)	(-1.44)	(-1.10)	(-0.67)	(-1.78)	(-1.94)						
Liquidity and Transaction costs												
ΔQuoted spread	0.062	-0.078	0.027	0.076	0.040	0.032	0.058	-0.136	-0.039	0.065	-0.004	-0.054
	(0.87)	(-0.78)	(0.25)	(0.77)	(0.60)	(0.49)						
ΔEffective spread	0.038	-0.017	-0.066	0.033	-0.007	0.057	0.111	0.029	0.009	0.145	0.018	0.026
	(0.49)	(-0.15)	(-0.46)	(0.33)	(-0.08)	(0.76)						
ΔEffective to quoted spread ratio	-0.032	0.041	-0.022	-0.014	-0.051	0.025	0.038	0.147**	0.096	0.074	0.012	0.085
	(-0.67)	(0.71)	(-0.35)	(-0.26)	(-0.86)	(0.44)						
ΔIntraday volatility	-0.258	-0.108	-0.231	-0.034	-0.015	-0.049	-0.203	0.046	-0.071	-0.068	0	-0.031
	(-1.12)	(-0.83)	(-1.03)	(-0.28)	(-0.13)	(-0.33)						

Panel II

	Cross listed						Adjusted (Cross listed − Matching)					
	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Trade Activity												
ΔTotal trade volume	-0.115	-0.081	-0.114	-0.147	0.014	0.054	-0.163	-0.049	-0.323*	-0.408**	-0.294*	-0.070
	(-0.82)	(-0.65)	(-0.69)	(-1.03)	(0.12)	(0.37)						
ΔAvg trade size	-0.116	-0.180**	-0.177	-0.175	-0.056	-0.191*	-0.109	-0.085	-0.424**	-0.358**	-0.314**	-0.314**
	(-0.73)	(-1.88)	(-1.08)	(-1.17)	(-0.42)	(-1.53)						
ΔQuote-to-trade ratio	-0.060	-0.106*	-0.127**	-0.051	0.031	-0.001	-0.049	-0.090	-0.157	-0.043	0.024	0.032
	(-1.04)	(-1.50)	(-2.09)	(-0.65)	(0.42)	(-0.02)						
Liquidity and Transaction costs												
ΔQuoted spread	-0.008	0.053	-0.013	0.059	0.024	-0.025	-0.054	-0.113	-0.108*	-0.058	-0.164*	-0.134
	(-0.12)	(0.61)	(-0.14)	(0.66)	(0.23)	(-0.24)						
ΔEffective spread	0.007	0.058	-0.047	0.003	0.030	-0.047	0.010	-0.105	-0.110*	-0.110	-0.130*	-0.187**
	(0.08)	(0.68)	(-0.55)	(0.04)	(0.32)	(-0.51)						
ΔEffective to quoted spread ratio	0.008	0.00	-0.020	-0.029	0.021	-0.004	0.046	-0.004	0.010	-0.035	0.032	-0.027
	(0.22)	(0.01)	(-0.49)	(-0.80)	(0.57)	(-0.08)						
ΔIntraday volatility	-0.104	-0.238	-0.177*	-0.237*	-0.001	-0.107	-0.170	-0.334	-0.140*	-0.288**	-0.114	-0.160
	(-1.18)	(-0.98)	(-1.48)	(-1.37)	(-0.01)	(-0.48)						

Table 5.2. Market quality changes after cross listing.
The table reports the changes for the cross listed firms and the differences in changes between these firms and their respective matches. Panel **I** presents the changes relative to the week before the announcement of the cross listing, for a sub-sample of twenty securities for which the time between the cross listing being announced and the commencement of trading on is exactly one week. In Panel **II**, changes are estimated for the full sample of twenty-six securities, relative to the month before trading commenced at A2X. ***, ** and * indicate statistical significance at the 1% , 5% and 10% levels respectively from a one sided t-test; t-statistics are shown in parentheses below the estimates.

generally not significantly different from those observed when trading commences at the destination venue. Interestingly, most of the results reported in the first six weeks after the announcement carry over to the six months after the cross-listings.

Monthly average changes in market quality are presented in Panel **II** of Table 5.2. As can be seen in the table, there is sparse evidence of statistically significant changes in the market quality of the cross-listed firms. That aside, trade activity decreases and transaction costs increase in most of the six months after cross-listing. Adjusting for the changes of the firms that do not cross-list, reveals significant differences in the changes of the two groups. For instance, relative to the firms that do not cross-list, there is a decline in trade activity. Changes in trade volumes and average trade sizes of cross-listed firms are respectively 5% to 41% and 9% to 42% less, in comparison to firms that do not cross-list. Moreover, the adjusted changes in trade volume are statistically significant in months three to five and the average trade sizes in months three through six. The evidence presented in Panel **II** suggests that there is a relative decline in transaction costs for the cross-listed firms as well.

It is apparent from Panel **II**, that changes in both quoted and effective spreads are generally greater for the matching firms that do not cross-list. Significant differences in quoted spreads are observed in months three and five and effective spreads in months three, five and six. Similarly, intraday volatility changes are less for the cross-listed firms than they are for the matching firms, suggesting that there is a relative improvement in pricing efficiency after cross-listing. However, significant adjusted changes are observed only in the third and fourth months. An interesting observation is that, in the first two months, none of the adjusted changes are statistically significant, suggesting that the effects of a cross-listing are not immediate.

Granted, cross-listings tend to increase inter-market competition that may in turn place downward pressure on prices. However, in the case of relatively illiquid securities, fragmenting an already small order flow may lead to information asymmetries that ultimately deteriorate pricing efficiency and make it more expensive for market makers to maintain their presence. In contrast, fragmenting the market of relatively liquid securities may bring about minimal changes in trade volumes, in which case, the benefits of the increased competition may outweigh any drawbacks associated with fragmentation. With these differences in mind, there is hardly any reason to expect that cross-listing will impact all firms equally.

Differences in Market Quality Changes Across Liquidity Groups

Changes in market quality after allocating firms into liquidity groups are reported in Tables 5.3 and 5.4. In Table 5.3, pre-cross-listing Amihud (2002) illiquidity measures are used to sort the firms into either one of two liquidity groups, and in Table 5.4, liquidity groups are defined by market segments. The market segments are a logical grouping of the instruments dictated by the instrument type and a liquidity rating; instruments are given a liquidity rating of 1, 2 or 3, determined by the average value traded per month over three months and the proportion of days traded in that period. The most liquid instruments are given a rating of 1 and the least liquid 3. All JSE listed equities fall into one of three segments. Specifically, ZA01, ZA02 and ZA03, with ZA01 being the most liquid; information in this regard is provided by the exchange.

Table 5.3. Market quality changes after cross-listing –Amihud illiquidity groups.
Market quality changes for the cross-listed firms and the adjusted changes are reported in this table. Cross listed firms are ranked and sorted into high and low liquidity groups defined by Amihud's illiquidity measure, averaged over the two months subsequent to the cross-listing announcement date. All changes are estimated relative to the month before trading commenced at A2X. ***, ** and * indicate statistical significance at the 1% , 5% and 10% levels respectively from a one sided t-test.

	Cross listed						Adjusted (Cross listed − Matching)					
	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Trade Activity												
ΔTotal trade volume												
High	−0.187**	−0.080	0.036	−0.066	0.012	−0.098	−0.106	0.000	−0.054	−0.050	−0.040	−0.046
Low	−0.042	−0.082	−0.264	−0.228	0.017	0.205	−0.219	−0.098	−0.592*	−0.767**	−0.628**	−0.095
Difference (High − Low)							0.113	0.098	0.538*	0.717**	0.667**	0.050
ΔAvg trade size												
High	−0.052**	−0.049	−0.021	−0.040	−0.109	−0.091	−0.038	−0.039	−0.088	−0.096	−0.104	−0.166*
Low	−0.180	−0.310**	−0.333	−0.310	0.03	−0.290	−0.179	−0.132	−0.760**	−0.621**	−0.524*	−0.470*
Difference (High − Low)							0.142	0.093	0.671*	0.526**	0.420	0.305
ΔQuote-to-trade ratio												
High	−0.018	−0.064	−0.184**	−0.135*	−0.106	−0.119	0.033	−0.025	−0.048	−0.006	0.059	−0.049
Low	−0.103	−0.148	−0.071	0.032	0.167*	0.117	−0.131	−0.151	−0.267	−0.081	−0.011	0.113
Difference (High − Low)							0.164	0.126	0.220	0.075	0.070	−0.162
Liquidity and Transaction costs												
ΔQuoted spread												
High	−0.102**	0.053	0.012	−0.025	−0.037	−0.134	−0.004	−0.019	−0.020	−0.076	−0.080	−0.133*
Low	0.085	0.054	−0.038	0.142*	0.084	0.084	−0.104	−0.206	−0.197*	−0.041	−0.250	−0.135
Difference (High − Low)							0.099	0.187	0.177	−0.035	0.169	0.002
ΔEffective spread												
High	−0.083**	0.064	−0.036	−0.090	−0.090	−0.171*	−0.004	−0.046	−0.071	−0.154**	−0.138*	−0.181**
Low	0.097	0.052	−0.058	0.097	0.148	0.076	0.025	−0.165	−0.149	−0.065	−0.123	−0.193*
Difference (High − Low)							−0.028	0.119	0.078	−0.089	−0.015	0.012
ΔEffective to quoted spread ratio												
High	0.028	0.017	−0.024	−0.023	−0.014	−0.026	0.013	−0.013	−0.027	−0.036	−0.022	−0.041
Low	−0.012	−0.016	−0.016	−0.035	0.055	0.019	0.079	0.005	0.047	−0.034	0.086	−0.013
Difference (High − Low)							−0.066	−0.018	−0.074	−0.002	−0.108	−0.029
ΔIntraday volatility												
High	−0.177***	0.025	−0.002	−0.087	0.015	−0.145	−0.051	−0.019	0.047	−0.028	0.047	−0.092*
Low	−0.032	−0.501	−0.351**	−0.388	−0.018	−0.069	−0.289	−0.648	−0.327**	−0.548*	−0.275	−0.227
Difference (High − Low)							0.238	0.629	0.373**	0.520*	0.322	0.135

Table 5.3 shows that for the high liquidity group of firms that cross-list, with the exception of the quote to trade and effective to quoted spread ratios, all other metrics decline significantly in the first month after cross-listing. However, these changes are not significantly different from the changes of the firms that do not cross-list. Moreover, for both liquidity groups, the changes observed in the first two months for the cross-listed firms are not significantly different from the changes of the firms that do not cross-list across all metrics. This finding is consistent with the results presented in Panel **II** of Table 5.2. Also worth noting, is that the magnitude of the adjusted changes is generally larger for the low liquidity group. For example, there is a 0% to 11% relative decline in trade volume for the highly liquid firms, whereas, for

the low liquidity group volume decreases by 10% to 77% over the six months after cross-listing. As it may be observed, the statistically significant adjusted changes in trade volume and average trade sizes of the low liquidity group coincide with the significant changes reported in Panel **II** of Table 5.2. It may therefore be the case that the significant and negative adjusted changes in trade activity following a cross-listing are associated with only relatively illiquid firms.

In addition, adjusted changes in transaction costs are generally negative in the six months after a cross-listing, as seen in Table 5.3. Although, there is limited evidence of persistent statistically significant changes over this period. The results indicate significant relative improvements in effective spreads for the high liquidity group of cross-listed firms in month four and every month after. However, a comparison between the Amihud illiquidity groups reveals that, with a few exceptions, there are no significant differences in the adjusted changes of the two groups. A similar set of results for each of the three market segments is reported in Table 5.4.

The estimates reported in Table 5.4 are largely consistent with the information previously presented in Table 5.3. Across all metrics the magnitude of the differences appears to increase with illiquidity, additionally, there is sparse evidence of an improvement in market quality across all market segments post-cross-listing.

Collectively, Tables 5.2, 5.3 and 5.4 present evidence of negative adjusted changes in trade activity and transaction costs after cross-listing. On one hand, the decline in trade activity points to a possible deterioration in market quality due to fragmentation. On the other hand, the reduction in spreads suggests that, on average,

Table 5.4. Market quality changes after cross-listing –market segments.
Market quality changes for the cross-listed firms and the adjusted changes are reported in this table. Each cross-listed firm is allocated into one of three liquidity groups determined by the average value traded per month over a three month period and the proportion of days traded in that same period. The most liquid firms are assigned to segment ZA01 and the least liquid ZA03. All changes are estimated relative to the month before trading commenced at A2X. ***, ** and * indicate statistical significance at the 1% , 5% and 10% levels respectively from a one sided t-test.

	Cross listed						Adjusted (Cross listed − Matching)					
	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Trade Activity												
ZA01	−0.168	0.126	0.080	−0.001	−0.098	−0.110	−0.071	0.077	0.018	0.001	0.144	−0.129
ZA02	−0.209**	−0.296**	−0.084	−0.119	−0.069	0.384*	−0.027	0.173	−0.055	−0.197	−0.029	0.584**
ZA03	0.095	0.021	−0.384	−0.358	0.048	−0.278	−0.481	−0.541*	−1.134**	−1.209**	−1.212**	−1.032
ΔAvg trade size												
ZA01	−0.034	0.012	0.109	0.073	−0.004	−0.001	−0.016	−0.001	0.009	−0.053	−0.046	−0.112
ZA02	−0.213**	−0.349**	−0.320**	−0.259*	−0.215	−0.129	0.026	−0.075	−0.109	−0.279**	−0.230*	0.012
ZA03	−0.057	−0.132	−0.280	−0.327	0.134	−0.504*	−0.426	−0.199	−1.414***	−0.832*	−0.751	−1.072**
ΔQuote-to-trade ratio												
ZA01	−0.035	−0.111	−0.113	−0.106	−0.149*	−0.129	0.001	−0.090	−0.079	−0.017	−0.040	−0.053
ZA02	−0.044	−0.015	−0.166**	0.052	0.143	0.010	0.075	0.068	−0.084	0.105	0.075	−0.070
ZA03	−0.116**	−0.243	−0.084	−0.152*	0.060	0.128	−0.303	−0.330	−0.362	−0.307*	0.017	0.290*
Liquidity and Transaction costs												
ΔQuoted spread												
ZA01	−0.066	0.119	0.059	−0.015	−0.019	−0.057	−0.050	−0.017	−0.045	−0.148*	−0.062	−0.006
ZA02	0.071	0.075	0.029	0.123	0.158	0.005	0.038	−0.111	−0.001	0.077	−0.026	−0.150*
ZA03	−0.067	−0.055	−0.159*	0.041	−0.138	−0.037	−0.204	−0.224	−0.351*	−0.171	−0.499*	−0.254
ΔEffective spread												
ZA01	−0.047	0.105	0.057	−0.015	−0.048	−0.084	−0.020	−0.023	−0.048	−0.164*	−0.110	−0.032
ZA02	0.063	0.089	−0.029	0.013	0.134	0.003	0.043	−0.098	−0.043	−0.075	−0.058	−0.236**
ZA03	−0.019	−0.045	−0.194**	0.008	−0.048	−0.084	−0.006	−0.210	−0.285*	−0.101	−0.267	−0.287
ΔEffective to quoted spread ratio												
ZA01	0.017	−0.008	0.004	0.003	−0.010	−0.023	0.030	−0.009	0.000	−0.014	−0.036	−0.033
ZA02	0.018	0.016	−0.031	−0.040	0.005	0.004	0.044	0.026	−0.013	−0.087**	0.013	−0.051
ZA03	−0.019	−0.015	−0.030	−0.047	0.081	0.006	0.067	−0.044	0.058	0.024	0.139	0.019
ΔIntraday volatility												
ZA01	−0.141*	0.190	0.011	−0.062	0.052	−0.072	−0.081	0.056	0.028	−0.091	0.057	−0.041
ZA02	0.013	−0.034	−0.082	0.023	0.122	0.111	−0.004	−0.030	−0.019	0.052	0.131	0.037
ZA03	−0.247	−1.047	−0.541**	−0.846*	−0.255	−0.489	−0.533	−1.257	−0.520*	−1.048**	−0.695	−0.604

the trading environment benefits from inter-market competition. However, evidence of statistically significant changes, on both absolute and relative bases, is limited. Based on these results, the hypothesis (H5.1) that market quality does not improve at the JSE after cross-listing on A2X, cannot be rejected. Moreover, there is sufficient evidence to reject the hypothesis (H5.2) that the effects of a cross-listing on market quality at JSE are related to the firm's pre-cross-listing liquidity characteristics. Results of similar tests carried out after alternating the length of the sample window for both event dates and winsorizing the top and bottom 1% observations are consistent and robust to these changes.

5.4.3 Cross-exchange Comparison

Relatively superior markets are typically characterised by environments where trades have less price impact, and the cost of immediately trading a given quantity is lower. Whether the JSE emerges as the dominant market after a cross-listing will therefore depend on the venue's ability to provide depth and competitive quoted spreads. This section compares market quality at the JSE and A2X over time in order to address the question of market dominance following a domestic cross-listing.

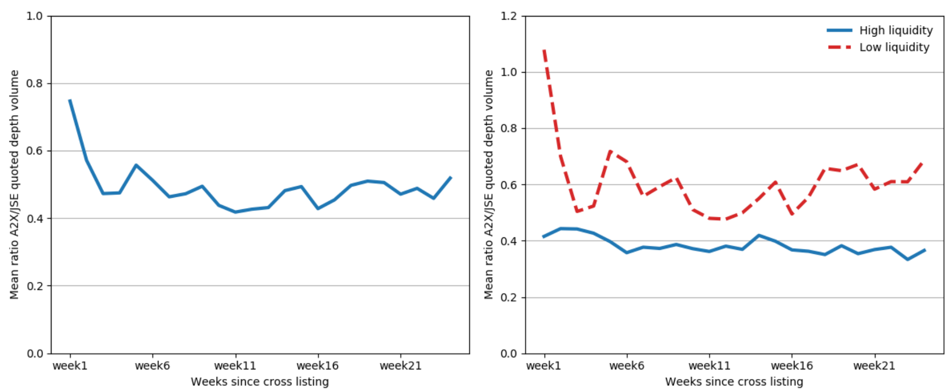


Figure 5.1. Mean pairwise ratios of weekly average quoted depth volume on A2X relative to JSE over the twenty-four weeks after cross-listing. The left panel consists of twenty-three firms that cross-list after January 2018 and the right panel separates the firms into high and low liquidity groups determined by the firm's Amihud ratio on the JSE, averaged over the two months prior to the cross-listing

Large quoted depth[8] values are associated with liquidity because markets are able to absorb sizeable order flow without moving prices dramatically. Figure 5.1 plots cross-sectional means of the pairwise ratios of weekly average quoted depth on A2X and the JSE, in the twenty-four weeks after cross-listing. The left panel of the figure covers all firms for which intraday data is available from the cross-listing date at both

[8]Quoted depth is defined as the time-weighted average of the total volume displayed at the bid-ask spread throughout the trading day

venues. On average, the quoted depth ratio is less than one, suggesting that the JSE has a more liquid trading environment than A2X does. In the first week after cross-listing, A2X is reported to have, on average, 75% of the quoted depth displayed at the JSE, and in subsequent weeks the ratio ranges between 42% and 57%. However, averaging across all firms conceals significant differences between liquidity groups.

Cross-sectional means of the quoted depth ratio are plotted separately for the high and low Amihud illiquidity groups, in the right panel of Figure 5.1. Generally, for both liquidity groups, there is more depth available at the JSE, consistent with the information in the left panel of the figure. Only in the first week after cross-listing is there relatively more volume quoted on A2X (7.8%) for the low liquidity group. Another observation worth noting is that the ratio is larger for the relatively illiquid firms throughout the entire twenty-four weeks. Bar the first week, quoted depth volume on A2X is on average, 48% to 72% of the JSE's for relatively illiquid firms. In contrast, the quoted depth ratio ranges between 33% and 44% for relatively liquid firms. The observed differences in quoted depth are complemented by significant differences in quote activity as well.

Cross-sectional means of the pairwise ratios of daily quote counts[9] averaged over a week, are presented in Figure 5.2. In the first seven weeks after cross-listing quoting activity at A2X is on average, 56% to 94% of activity at the JSE. Thereafter, the ratio stabilises ranging between 50% and 65%. The right panel of Figure 5.2 reveals that the large variation is likely caused by the relatively illiquid firms, suggesting

[9] A count of the number of times the prevailing quote is updated i.e. any change in the best bid or best ask price, or the order size at these prices.

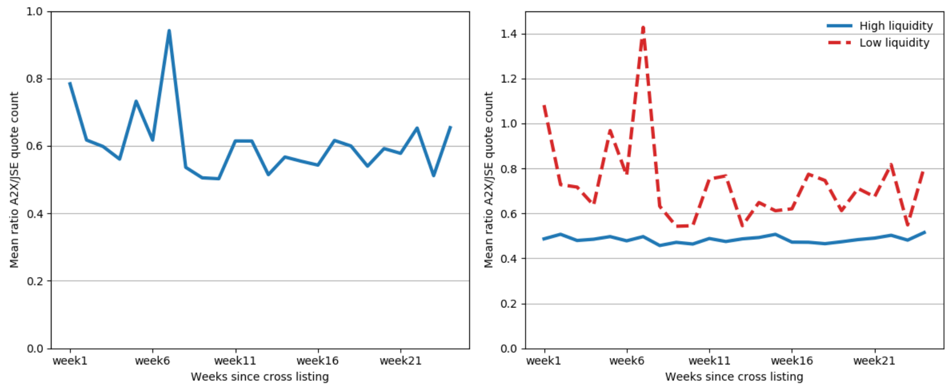


Figure 5.2. Mean weekly ratio of A2X to JSE quote activity over the twenty-four weeks after cross-listing. The left panel consists of twenty-three firms that cross-list after January 2018 and the right panel separates the firms into high and low liquidity groups determined by the firm's Amihud ratio on the JSE, averaged over the two months prior to the cross-listing

that quoting activity is more consistent for liquid firms. Interestingly, in the first week, the quote activity of the illiquid firms is 8% larger on A2X, almost equal to the relative size of the quoted depth shown in Figure 5.1. Moreover, the ratio is strictly larger for illiquid firms in comparison to liquid firms. Together, Figures 5.1 and 5.2 provide strong evidence of the JSE's ability to provide more depth in comparison to A2X. Hence, relative transaction costs will determine whether the JSE can be designated as the dominant market.

The results of univariate tests comparing transaction costs at the two trading venues are presented in Table 5.5. Specifically, the table reports mean pairwise spread and volatility ratios over the six months after cross-listing. As can be seen, both quoted and effective spreads are generally significantly larger at A2X in comparison to the JSE. In contrast, intraday volatility at A2X is on average 23% to 33% significantly less than the JSE. This result is unsurprising, as the lower volatility is consistent with the differences in quote activity illustrated in Figure 5.2. It is also worth noting that in comparison to the JSE, A2X quoted spreads are significantly larger only for relatively illiquid firms. Conversely, there generally are no significant differences in effective spreads for the relatively illiquid firms, whereas significant differences are reported for the liquid firms.

Moreover, the effective spread ratio of the liquid firms is generally larger than that of the illiquid firms. This finding can be explained, in part, by the differences in quoted depth displayed in 5.1. The figure shows that relative to the JSE, A2X has lower quoted volumes. Consequently, fulfilling a sizeable order will typically exhaust more levels of the order book at A2X than at the JSE, and because higher levels have higher prices, average execution costs will be greater at A2X. Considering that A2X quoted volumes are closer to the respective JSE values for illiquid firms than they are for liquid firms, relative differences in effective spreads will be greater for liquid firms. In essence, the results presented in Table 5.5 provide strong evidence that points to transaction costs being lower at the home market after a cross-listing.

Table 5.5. Liquidity differences across markets.
Liquidity differentials between markets for a sample of twenty-three JSE firms that are cross-listed on A2X are reported in this table. The results are reported for the full sample and sub-samples determined by the firms liquidity characteristics. ***, ** and * indicate statistical significance at the 1% , 5% and 10% levels respectively from a one sided t-test.

	A2X/JSE					
	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Quoted spread	1.12	1.31	1.36**	1.41**	1.38**	1.94**
High liquidity	0.94	1.46	1.23	1.35	1.04	1.10
Low liquidity	1.30**	1.16	1.50*	1.48**	1.75**	2.85**
Effective spread	2.09***	2.71***	2.08***	1.83***	1.93***	2.47**
High liquidity	2.72***	3.31***	2.43***	1.71***	2.05***	2.36***
Low liquidity	0.95	1.09	1.25	2.07**	1.69	2.69
Intraday volatility	0.72***	0.70***	0.77***	0.67***	0.73***	0.71***
High liquidity	0.69***	0.72***	0.71***	0.71***	0.70***	0.74***
Low liquidity	0.75***	0.70***	0.84	0.62***	0.76**	0.66***

In a multi-market trading environment, informed traders will often conceal their trades in the relatively liquid market and liquidity traders will typically trade at the venue that provides lower transaction costs. Consequently, activity is unlikely to be evenly distributed between venues. Together, Table 5.5 and Figure 5.1 show that in the post cross-listing environment, there is more liquidity available at the JSE, in addition to the venue having lower transaction costs. Accordingly, trade volume is expected to concentrate at the JSE. Figure 5.3 plots the cross-sectional means of the ratios of weekly average volume traded. As anticipated, significantly more order flow is executed at the JSE. Throughout the entire twenty-four weeks after a cross-listing, A2X's share of executed volume is never more than 1% of the JSE's. Furthermore, the relative volume is generally greater for low liquidity firms, in line with the evidence presented in Table 5.5 and Figure 5.1.

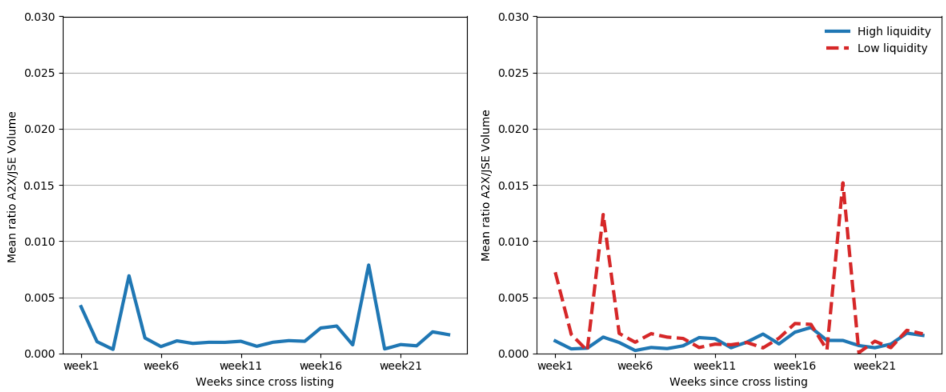


Figure 5.3. Mean weekly ratio of A2X to JSE volume traded over the twenty-four weeks after cross-listing. The left panel consists of twenty-three firms that cross-list after January 2018 and the right panel separates the firms into high and low liquidity groups determined by the firm's Amihud ratio on the JSE, averaged over the two months prior to the cross-listing

Evidence presented in this section shows that, albeit the sizeable quote activity on A2X, trading remains largely concentrated at the JSE. These observations validate the argument that the home market will be the dominant venue in the multi-market environment created by cross-listings. As there is no evidence of the migration of volume to A2X, equal in magnitude to the JSE decline reported in Section 5.4.2, the results further suggest that the lower trade volume is likely unrelated to the decision to cross-list.

5.4.4 Best Execution in a Fragmented Market

A rudimentary assessment of whether the draft Conduct Standard for Exchanges would have the desired impact on the quality of the multi-market trading environment is undertaken in this section. Specifically, a comparison is made between the spread and depth values at each venue, and the NBBO values predicated on a consolidated order book. The dataset used in this part of the analysis consists of order book data for the last full trading day of each month in the thirty-three month period starting in January 2018. When building the consolidated order book, strict price-time priority across venues is maintained as well. To illustrate the relevance of best execution standards, consider the following brief analysis of the distribution of trade volumes.

Currently, institutional structures do not provide for protection against trade-throughs. A trade-through occurs when a venue executes a trade at a price that is inferior to the best price displayed by another trading venue (Securities and Exchange Commission, 2005) for that same security. Figure 5.4 presents a plot of the frequency of trade-throughs at the JSE over time. The left panel of the figure reveals that, after taking trade directions into account, 30% to 77% of trades executed at the JSE are

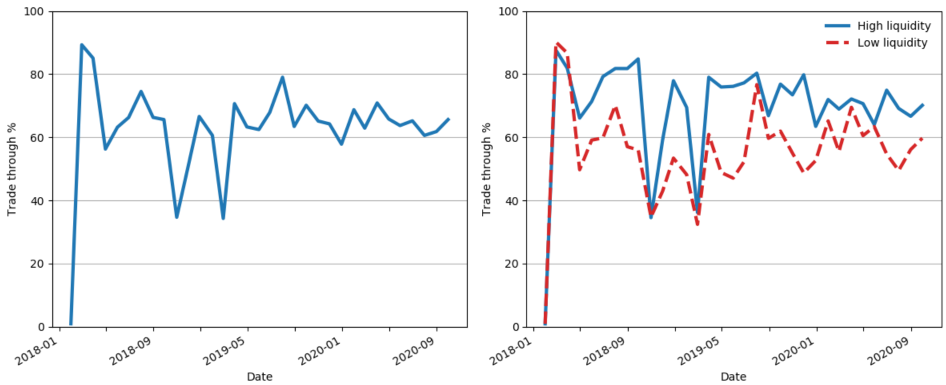
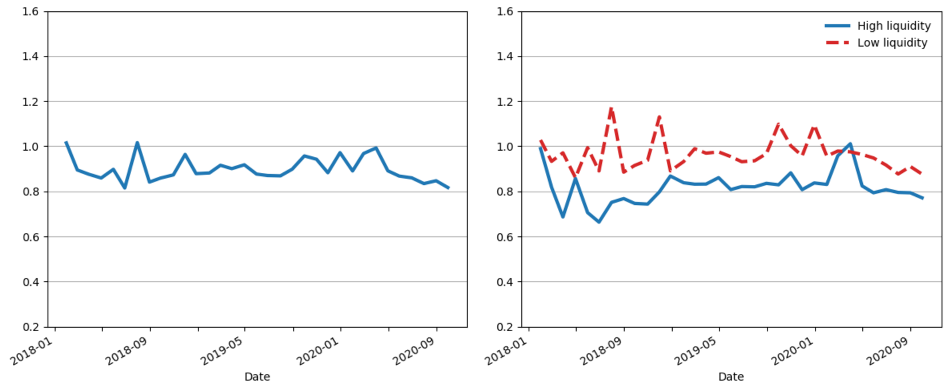


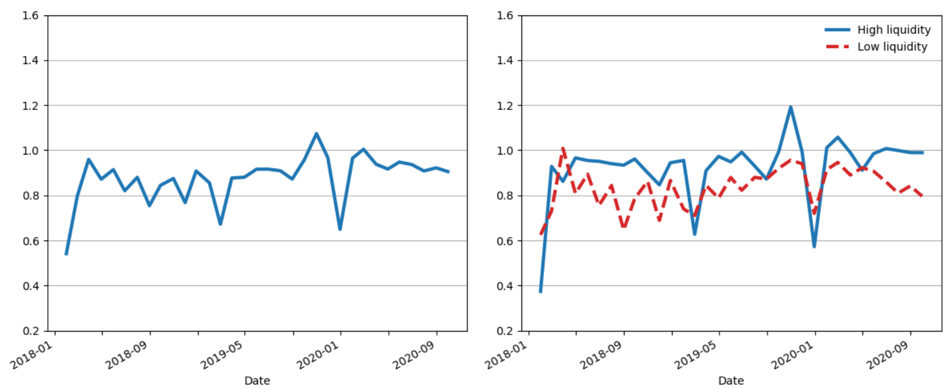
Figure 5.4. Average JSE trade-through percentages. The daily measure for each security is calculated by dividing the total number of trade-throughs for that security by the total number of trades on that day. A trade through occurs when an order is routed to the JSE for execution in spite of the fact that A2X has a higher (lower) bid (ask) price. The values shown are the cross sectional averages across all cross-listed firms on that date

executed when A2X has a higher (lower) bid (ask) price. Moreover, as can be seen in the right panel, trade-throughs occur approximately 1.6 times more frequently for relatively liquid firms than they do for illiquid firms. This observation is consistent with the view that the order flow of illiquid securities generally concentrates at the top of the order book, whereas liquid securities have more depth in the order book as order flow is distributed across multiple price levels. A sizeable order submitted at one venue, is therefore less likely to be fulfilled at a price inferior to the best available at another venue, for illiquid securities than it is for liquid securities. The high incidence of trade-throughs raises questions about cost advantages for participants with access to both venues, versus those only trading on a single exchange.

A comparison between the NBBO quoted spreads and the quoted spreads at the JSE and A2X is made in Figures 5.5a and 5.5b. A ratio of less than one indicates that, on average, when trading in the equities of a cross-listed firm, there would be a cost advantage to filling orders across both venues, relative to routing order flow to



(a). NBBO quoted spread ratio - JSE



(b). NBBO quoted spread ratio - A2X

Figure 5.5. Mean NBBO quoted spread ratio. The daily measure is calculated by dividing each security's NBBO quoted spread by the quoted spread. All spreads are time weighted. The values shown are the cross sectional averages across all cross-listed firms on that date

just that venue. The left panel of Figure 5.5a shows that NBBO quoted spreads are on average, 84% to 102%[10] of JSE quoted spreads. Similarly, Figure 5.5b illustrates that NBBO spreads are 54% to 107% of quoted spreads at A2X. Panel **I** of Table 5.6 presents the results of a univariate analysis of the NBBO spread ratios. The

[10]In theory, the NBBO quoted spread should be less than or equal to the spreads displayed across all venues. However, in instances where one venue has a valid quote displayed for a greater portion of the trading day, relative to the other venue, the time-weighted NBBO can be greater than the quoted spread at one venue, and less than the value estimated at the other venue.

second column of the table indicates that using the consolidated order book provides a statistically significant cost advantage, of approximately 10%, relative to using either one of the venues exclusively.

Table 5.6. NBBO quoted spread and depth ratios.
This table presents the average of the NBBO spread (depth) divided by the quoted spread (depth) at the JSE and A2X, starting in January 2018 until September 2020. The ratio is calculated for each firm on the last trading day of each month and then averaged across the entire sample of firms across time. Results are reported for the full sample and sub-samples determined by the firm's pre-cross-listing liquidity characteristics. The table also reports difference of mean tests between liquidity groups and across venues. ***, ** and * indicate statistical significance at the 1% , 5% and 10% levels respectively from a two sided t-test, where the null hypothesis is that the ratio is equal to 1.

	Full sample	High liquidity	Low liquidity	Difference (High - Low)
Panel I - Quoted spread				
JSE	0.8974***	0.8303***	0.9646**	−0.1343***
A2X	0.8976***	0.9486***	0.8466***	0.1020***
Difference (JSE - A2X)		−0.1184***	0.1179***	
Panel II - Quoted depth				
JSE	0.5718***	0.4124***	0.7363***	−0.3238***
A2X	1.7368***	1.0623***	2.3887***	−1.3263***
Difference (JSE - A2X)		−0.6450***	−1.6524***	

The results reveal that across both exchanges, there is a difference in cost advantages for each of the liquidity groups. The right panel of Figure 5.5a shows that, at the JSE, cost reductions are larger for the liquid group of securities. In contrast, at A2X, the low liquidity group would benefit more from consolidating the order books, as can be seen in Figure 5.5b. Furthermore, Table 5.6 shows that for the high liquidity group, cost reductions will be greater at the JSE than A2X, whereas, for the low liquidity group, cost reductions are greater at A2X. Panel **I** of Table 5.6 reports the results of similar tests on the NBBO quoted depth ratio. The evidence indicates that relative to A2X, the consolidated order book has significantly greater volume displayed at the best quote. While in comparison to the JSE, the consolidated order book has significantly less quoted depth. This result is unsurprising, given the evidence presented in Figure 5.1. It is worth noting that, for market participants currently trading exclusively at the JSE, switching to a consolidated order book would not necessarily imply a deterioration in liquidity, but rather, price impact increases due to A2X's superior prices having lower associated volumes.

All things considered, the evidence supports the conclusion that, in comparison to A2X, the NBBO market for cross-listed securities is superior. However, a similar conclusion cannot be drawn with respect to the JSE, as the NBBO market only presents a cost advantage. Overall, results reported in this section demonstrate that increasing interoperability between venues, by consolidating their respective order books, may significantly improve the price dimension of execution quality for cross-listed firms.

5.5 Summary

The results of an investigation of market quality changes, for a sample of JSE listed firms that cross-listed on A2X between 2018 and 2020, are reported in this chapter. A matched sample design is used to adjust the market quality measures for the contemporaneous changes of firms that do not cross-list. The results report limited evidence of reductions in trade activity at the JSE in the six months after cross-listing and weak evidence of improved spreads. Additional univariate empirical tests refute the view that the impact of cross-listing varies with a firm's pre-cross-listing liquidity characteristics. And further analysis suggests that cross-listing does not result in a permanent improvement of the market quality measures considered. The evidence reported in this chapter also lends support to previous theories on the dominance of the home market after a cross-listing, as indicated by lower transaction costs and greater depth at the JSE. Furthermore, in addressing the resulting fragmentation by consolidating the domestic markets for a firm's cross-listed securities, it is revealed that quoted spreads would improve significantly. Everything considered, it can be concluded that having access to consolidation tools and establishing NBBO regulatory requirements may positively impact market quality across both trading venues.

Chapter 6

Conclusion

In summary, three empirical studies that address various questions related to market quality, design and stability in the South African equity market are presented in this thesis. What is known about each of the identified research areas is largely based upon empirical studies that look at the larger, more developed financial systems. Collectively, the studies contribute to ongoing discussions in the identified literature streams, for the benefit of regulators, policymakers and market participants in emerging economies. The primary research questions of the first two components, documented in Chapters 3 and 4, advance research in the area of market stability, where it pertains to systemic risk and information contagion. And Chapter 5 considers recent regulatory developments that effectively fragmented the equity market, and the impact these microstructure changes have had on market quality.

6.1 Summary of Findings

Chapter 3 engages with the literature on the measurement of systemic risk using market-based measures. As markets have continued to grow and increase in their complexity, financial stability has remained at the forefront of the regulatory agenda globally. Traditional supervisory instruments are however known to be flawed for a number of reasons. For example, microprudential tools may be subverted by institutions engaging in regulatory arbitrage, and the frequency at which balance sheet information is made available presents a further challenge to the real-time monitoring financial systems. The global financial crisis of 2008 highlighted these challenges and called further attention to the need for tools better equipped to assess the soundness of financial systems in a timely and accurate manner, in order to support oversight and inform policy decisions.

This study employs systemic risk measures introduced in the seminal work of Acharya et al. (2017) and Brownlees and Engle (2017), to investigate questions related to differences in the systemic risk contributions of sectors, and the implications of interconnectedness for spillovers between sectors. Attention is also given to the view that capital shortfalls in the banking sector may spill over into the real economy through lending activity. The first measure, MES, defined as the short-run expected equity loss conditional on the market taking a loss greater than its Value-at-Risk, has been shown to have a strong association with a firm's propensity to be undercapitalized when the system as a whole undercapitalized. SRISK on the other hand measures capital shortfalls conditional on a severe market decline. Both measures are estimated at a daily frequency, starting in 2003 until the end of 2018, for a sample of 125 financial institutions listed on the JSE. What follows an analysis of the time-series behaviour of the measures to address the identified research questions and establish whether they may be of any use to regulators, policymakers in South Africa.

In general, the evidence indicates that the average level of systemic risk has increased over time, consistent with global trends and the widespread increases in complexity of financial systems. Further analysis reveals that systemic risk predominantly resides with banking institutions. However, this result is not particularly surprising given the fact that existing literature has hypothesized, and shown, that banks will on average contribute more to systemic risk because they typically exhibit the highest levels of leverage, relative to other financial institutions. In fact, the evidence validates the hypothesis that banking and insurance institutions are collectively the largest contributors to systemic risk, as this is symptomatic of the prevailing market conditions. One unanticipated finding is the apparent inability of SRISK to capture systemic risk spillovers associated with high levels of interconnectedness and significant common exposures.

Results obtained from pairwise predictive regressions reveal that increases in expected capital shortfalls are not propagated across the financial sector. Instead, we observed that increases in SRISK in one sector generally forecast decreases in SRISK in other sectors. What is also intriguing, is that only the banking sector has significant forecasting ability for changes in other sectors. Additional checks are conducted to assess the consistency of the systemic importance implied by SRISK and MES with traditional regulatory measures of systemic importance. All rank correlations between the estimated measures and a set of firm characteristics widely used as indicators of systemic importance are positive and statistically significant. By providing new evidence of structural breaks in the periods surrounding significant market events, the study also demonstrates the sensitivity of SRISK and MES to prevailing market conditions. Lastly, further contributions are made to the literature by illustrating the causal relationship between SRISK in the banking sector and the prime lending rate. This result complements previous evidence of systemic risk spillovers into the real economy; including a study in which Allen et al. (2012) demonstrated that high levels of systemic risk in the banking sector may impact lending activity by reducing the size of aggregate loans.

Some limitations of the research design need to be acknowledged in the interpretation of these findings. Perhaps the most salient shortcoming has to be that the public equity market does not cover the entire financial system. For instance, of the thirty-three licensed banks, only seven are listed and traded at the JSE. Furthermore, high-frequency market data is not available for money market funds and CISs, both of which are known to play an important role as financial intermediaries in South Africa's economy. Any market-based measure of systemic risk is therefore unlikely to provide a comprehensive assessment of financial stability. Notwithstanding these limitations, the usefulness of both MES and SRISK for monitoring stability in the South African financial sector is clearly supported by the current findings.

The next study, presented in Chapter 4, builds on two streams of empirical research. The first is a relatively new but growing body of literature that identifies crowding as a potential amplifying channel for price instability and volatility spillovers. The concern, for the most part, stems from (i) the self-reinforcing downward price pressure resulting from the liquidation of concentrated positions, and (ii) the deterioration in liquidity due to congestion that arises on one side of the market. Externalities generated by crowded trades may therefore adversely affect market efficiency. The second stream of research is concerned with information contagion and documents how investor attention plays a role in the diffusion of information between firms. Particularly, how firm-specific developments may have significance for other firms, in that this information may be partially or fully mirrored in firms that can be linked either through return predictability or otherwise considered as peers. A series of recent events in South Africa's capital markets presents a unique opportunity to examine these two streams where they intersect.

Using a panel dataset that consists of 416 JSE listed firms over the seven years starting in 2014, the study examines how crowding, liquidity and systemic risk interact in the equity market. Specifically, an investigation of return predictability between firms is carried out, the results of which are used to identify, for each firm, an information network of follower firms. An assessment of the sensitivity of these networks to firm-specific developments is followed by a series of event studies aimed at addressing questions around the consequences of misconduct contagion for the trading environment. To estimate crowding, we propose a metric based on trading volume data that identifies trade directions. Additional tests are carried out in which the effects that crowding has on liquidity and the tail of returns distributions are examined as well.

It is a widely held view that return predictability can be attributed, in part, to information being incorporated faster into the share values of firms with greater levels of investor attention. Reasoning from this fact, one would expect the same to hold where investor attention increases due to firm-specific developments. The evidence reported in Chapter 4 confirms that firm-specific developments have a significant impact on the size of a firm's information network of followers, even after controlling for other factors that can be expected to influence investor attention. However, in contrast to previous findings, there is strong evidence of a decline in a firm's number of followers as attention related to firm-specific developments —proxied by news counts —increases. Hence, one can reasonably assume that investor attention associated with firm-specific developments hinders return predictability. This, in turn, could be interpreted as evidence of firm-specific information having an impact on the trading environment of the firm's information network of followers as well.

As anticipated, the findings conform to the hypothesis (H4.1) that crowding increases for firms facing allegations of misconduct or wrongdoing. Similarly, for the identified information networks, significant changes in crowding are observed in the post-event period. Although this result agrees with previous conjectures related to misconduct contagion, the observed outcome is not as expected. Instead, the results indicate that crowding declines significantly for both information followers and industry peers. The hypothesis (H4.2) that crowding increases for firms with links to the tainted firms can be therefore rejected. The reasons for this rather contradictory result are not yet clear. In contrast, for a sample of rand-hedges, crowding is reported to increase on most days following allegations of malfeasance, however, only the large negative changes are statistically significant.

In addition, the study documents evidence of coincidental and significant changes in trade volume, quoted spreads and MES in the post-event periods. Thus, it seems natural to question the causal effects of crowding on systemic risk and liquidity. A multivariate panel regression analysis reveals that the proposed measure of crowding has significant explanatory power for both MES and quoted spreads. This finding demonstrates that crowding increases exposure to adverse spillover effects and deteriorates liquidity. Consequently, we fail to reject the hypothesis (H4.4) that crowding increases systemic risk. Perhaps the most intriguing result pertains to the new evidence of the asymmetric effects that intraday volatility and trade volumes have on MES and quoted spreads. It is shown that intraday volatility forecasts greater increases systemic risk when there is a sell-crowd than it does when there is a buy-crowd. Similarly, the volume traded forecasts a larger improvement in liquidity for buy crowds than it does for sell crowds.

Regarding the research methods, there are limitations to be acknowledged here as well. A potential source of bias in the study is the limited availability of the news data used to make an inference on how firm-specific information flows between firms. Furthermore, an inherent limitation, in the nature of the proposed measure of crowding is that it fails to take unobserved interactions between market participants into account. Nevertheless, the results presented here enhance our understanding of the implications of misconduct contagion and crowding in the South African equity market.

The next chapter moves on to discuss recent regulatory reforms that led to structural changes in the design of South Africa's capital markets, effectively altering the ways in which agents can interact. With the proliferation of new exchanges that has since occurred, several firms have taken up the opportunity to cross-list their shares on multiple local venues. While firms often list their shares in more than one jurisdiction, doing so domestically is rare. In earlier years, the literature documented that domestic cross-listings do not result in a significantly improved liquidity environment. Moreover, there is limited evidence related to domestic cross-listings beyond their impact on firm values, as researchers shifted their focus to international cross-listings early on during the waves of consolidation that swept through the developed markets. The study in Chapter 5 is also motivated by previous research that has provided extensive evidence on the counteracting effects of fragmentation and inter-market competition. On one hand, changes in liquidity and volatility associated with order flow migration following cross-listing may adversely affect market quality. On the other hand, increased inter-market competition may place downward pressure on the cost of trading across venues.

We use intraday data to investigate the impact of domestic cross-listings for a sample of twenty-six JSE listed firms that cross-listed on A2X between April 2018 and April 2020. Market quality measures considered include: quoted and effective spreads, volume traded, intraday volatility and quote-to-trade ratios. The study also questions whether a firm's pre-cross-listing liquidity characteristics determine the significance of market quality changes at the JSE. More importantly, after rebuilding a consolidated order book based on a simple set of best execution rules, we evaluate whether the post-fragmentation trading environment would benefit from NBBO regulations.

Adjusting the market quality measures for the contemporaneous changes of a matched sample of firms that do not cross-list provides weak evidence to support the view that domestic cross-listings improve market quality. The main findings show that relative to firms that do not cross-list, there is a significant decline in trade activity at the home market. Cross-listing theory has previously identified that a decline in trade activity is likely a consequence of the diversion of order flow to alternative venues. However, further analysis reveals that a negligible fraction of total volume executed (approximately $< 1\%$) can be attributed to activity at A2X. Therefore, it is plausible that JSE trade activity declines for reasons related to a firm's decision to cross-list but unrelated to the diversion of order flow. At the same time, spreads generally increase after cross-listing. However, these increases are neither large nor statistically significant. Nevertheless, relative to the matched sample of firms that do not cross-list, the evidence indicates an improvement in spreads after cross-listing, providing weak support for the view that inter-market competition places downward pressure on transaction costs.

Moreover, the results do not indicate significant differences in responses to the announcement of a cross-listing and the commencement of trading at alternative venues. This observation is relevant on the basis that, if the efficient market hypothesis holds, the market should react to news of the expected microstructure changes on the announcement date. However, in a multi-market environment, the split of order flow effectively only occurs when a stock begins trading at both venues. We find that trade volume decreases, on average, by 42% less in the week immediately after the announcement and before the cross-listing. Over the same period, we do not find any significant changes in transaction cost. When trading commences in the following week, only the quote to trade ratio declines significantly. After controlling for the changes of the matched sample, the evidence does not indicate significant differences in the market's response. Another interesting observation is that across all the market quality metrics considered, there are no significant relative differences in the first two months after cross-listing. It can thus be hypothesised that significant changes in market quality following a cross-listing, are not immediate.

Prior research has shown that in both instances of international and domestic cross-listings, pre-listing liquidity characteristics play a role in the significance of the impact that cross-listing has on firm values. However, it is apparent from the results that these findings do not extend to the market quality measures considered here. The results show that, despite the adjusted changes of the relatively illiquid firms being larger in general, compared to liquid firms, the changes observed for the two groups are not significantly different. This evidence is sufficient to reject the hypothesis (H5.2) that the effects of a domestic cross-listing vary with a firm's pre-cross listing liquidity characteristics. On the question of market dominance in the post-cross-listing multi-market environment, the evidence is consistent with the existing theories considered in formulating the hypothesis H5.3.

Results show that the JSE retains a significantly larger share of the executed order flow after a cross-listing. These disparities in trade activity can be attributed to significantly lower quoted spreads and greater quoted depth at the JSE. The observed differences are therefore unsurprising, in view of the fact that all else equal, order flow is generally routed to the venue with the least likelihood of executing trades outside the prevailing quote. Most importantly, it is shown that the use of consolidation tools or implementation of NBBO regulations can positively impact market quality. Specifically, the evidence indicates that relative to A2X, market quality in a NBBO market would be significantly superior. In contrast, the NBBO market has lower quoted spreads and quoted depth relative to the JSE. The latter result is expected, on account of A2X's superior prices having lower associated volumes. From these results, we conclude that improvement in market quality after a domestic cross-listing is conditional on interoperability between venues.

Inferences made from the results presented in the cross-listing study are subject to at least two caveats. First, as the wave of fragmentation is still in the early stages, the assessment is made using a relatively small sample of securities. The generalisability of the findings may therefore be limited. Second, a rudimentary definition of best execution is used in the assessment of the potential benefits of interoperability. In reality, execution quality is not only subjective but also has multiple facets outside of the price dimension.

6.2 Directions for Future Research

Quite a few interesting issues for further research are raised by the work presented in this thesis. For instance, more research is needed to provide an understanding of the implications of the high levels of interconnectedness and concentration for systemic risk spillovers in South Africa's financial sector. The study could further be extended by investigating the factors driving the observed changes in relative contributions of the sectors over time. A natural progression of the crowding study is to investigate whether positive firm-specific news has similar consequences for the firm and its information network. It would equally be worthwhile to consider a measure of crowding that not only takes into account the investor sentiment implied by observable trade activity, but also reflects the extent to which market participants have similar holdings. Forthcoming studies in the cross-listing literature could also interrogate the roles played by domestic cross-listing venues in the price discovery process. Furthermore, it would be a valuable extension to simulate trading activity using multiple iterations of best execution standards.

Appendix A

A.1 Time-varying Conditional Correlation

To allow for asymmetries, time varying conditional correlations between $r_{i,t}$ and $r_{m,t}$ are estimated using a modified DCC approach, in very much same way as Cappiello et al. (2006). The covariance matrix, Σ, is therefore equivalent to

$$\Sigma_t = D_t R_t D_t,$$

where $R_t = \begin{bmatrix} \rho_{i,t} & 1 \\ 1 & \rho_{m,t} \end{bmatrix}$ is the dynamic correlation matrix and $D = \begin{bmatrix} \sigma_{i,t} & 0 \\ 0 & \sigma_{m,t} \end{bmatrix}$. The matrix R_t is then decomposed using a pseudo-correlation matrix Q_t, such that

$$R_t = diag(Q_t)^{-\frac{1}{2}} Q_t diag(Q_t)^{-\frac{1}{2}}.$$

As outlined by Idier et al. (2014), Q_t is given by

$$Q_t = (1 - a - b)S - gN + a\eta_{t-1}\eta_{t-1}^{'} + gu_{t-1}u_{t-1}^{'} + bQ_{t-1}.$$

The quantities a, b and g are scalars that define the conditions under which Q_t is a positive definite matrix—$a > 0$, $b > 0$, $g > 0$ and $a + b + \delta g < 1$; δ is defined by the maximum eigenvalue of the matrix $S^{-\frac{1}{2}} N S^{-\frac{1}{2}}$; η_t is the vector of standardized returns i.e. $(\epsilon_{i,t}\epsilon_{m,t})^{'}$; $u_t = \eta_t \mathbb{I}_{\eta_t < 0}$; and S and N are intercept matrices, estimated as

$$\hat{S} = \frac{1}{T}\sum_{t=1}^{T} \eta_t \eta_t^{'}$$
$$\hat{N} = \frac{1}{T}\sum_{t=1}^{T} u_t u_t^{'}.$$

The asymmetric DCC model is generally estimated using two-step quasi-maximum-likelihood methods.

A.2 Estimating Tail Expectations

Equation 3.1 also reveals that MES depends on the tail expectations of the disturbances $\varepsilon_{m,t}$ and $\xi_{i,t}$. Specifically, these quantities are $E_{t-1}\left(\varepsilon_{m,t} | \varepsilon_{m,t} < \dfrac{C}{\sigma_{m,t}}\right)$ and $E_{t-1}\left(\xi_{i,t} | \varepsilon_{m,t} < \dfrac{C}{\sigma_{m,t}}\right)$. Following the procedure of Brownlees and Engle (2017), a non-parametric kernel estimator is used, in order to avoid instability when $\frac{C}{\sigma_{m,t}}$ is large. If we let

$$K_h(t) = \int_{\infty}^{\frac{t}{h}} k(u)du,$$

such that $k(u)$ is a kernel function, and h some positive bandwidth, the tail expectations can therefore be estimated using the following discrete approximations:

$$E_{t-1}\left(\varepsilon_{m,t}|\varepsilon_{m,t} < \kappa\right) = \frac{\sum_{j=1}^{t-1} \varepsilon_{m,j} K_h(\varepsilon_{m,j} - \kappa)}{(t-1)\hat{p}_h}$$
$$E_{t-1}\left(\xi_{m,t}|\varepsilon_{m,t} < \kappa\right) = \frac{\sum_{j=1}^{t-1} \xi_{m,j} K_h(\varepsilon_{m,j} - \kappa)}{(t-1)\hat{p}_h},$$

where $\hat{p}_h = \dfrac{\sum_{j=1}^{t-1} K_h(\varepsilon_{m,j} - \kappa)}{t-1}$. This non-parametric method also leaves the model flexible enough to accommodate the mixture of distributions that are likely to prevail over the sample.

Appendix B

B.1 Variable Definitions

Analyst coverage –number of sell-side analysts covering the security, computed using the I/B/E/S dataset. This is a monthly-frequency variable.

Institutional ownership –the fraction of total shares outstanding owned by institutions. Excludes ownership by individual and insider investors. This is a monthly-frequency variable.

Momentum –cumulative return of a stock over a period from the beginning of month t_{-13} to the end of month t_{-2} as per Jegadeesh and Titman (1993). This is a monthly-frequency variable.

Price-to-book ratio –closing price divided by book value per share. Book value per share is calculated by dividing the total equity from the latest fiscal period by the current total shares outstanding. This is a daily frequency variable.

Price-to-earnings ratio –ratio of the share price relative to its earnings per share. This is a daily frequency variable.

Size –market capitalization; calculated as the product of a stock's share price and the number of shares outstanding. This is a daily frequency variable.

Volume –total quantity of shares traded. This is a daily frequency variable and unless specified otherwise, the daily measure is then averaged over a rolling 250 trading day period.

Turnover –rand value of a stock's total volume traded. This is a daily frequency variable and unless specified otherwise, the daily measure is then averaged over a rolling 250 trading day period.

B.2 Misconduct Events

Steinhoff International Holdings

6 December 2017 –Two days after announcing that its 2017 audited financial results would be delayed, Steinhoff announces that they are launching an investigation into accounting irregularities and the immediate resignation of the CEO. Investors are subsequently informed that the already published 2016 financials would have to be

restated and could not be relied on. On 15 Mar 2018, a report published by PricewaterhouseCoopers details how the firm recorded fictitious or irregular transactions totalling 6.5 billion euros over a period covering the 2009 and 2017 financial years.

Tongaat Hullet

31 May 2019 –After issuing multiple cautionary announcements to shareholders, advising that a strategic and financial review has revealed concerning past practices, Tongaat Hullet confirms that the results for the 2018 financial year are to be restated, as they did not reflect the company's business performance. An investigation by PricewaterhouseCoopers later revealed that executives inappropriately capitalised assets, recognised revenues in earlier reporting periods than they should have and inappropriately capitalised expenses as assets. Ultimately Tongaat was found to be in contravention of the Companies Act, as they overstated profits and misrepresented information to shareholders.

EOH Holdings Ltd

18 February 2019 –A SEC corruption complaint involving EOH surfaces. It is revealed that a whistle-blower lodged the complaint with the SEC at the end of November 2018 under the anti-graft legislation. The allegations are made regarding a contract awarded by the South African Department of Defence in 2016 to the EOH subsidiary, EOH Mthombo. An investigation by ENSafrica found evidence of (i) tender irregularities (ii) EOH employees conspiring with preferred suppliers to inflate

software licence sales, and (iii) inappropriate sponsorships and donations.

Aspen Pharmacare

14 August 2019 –Aspen agrees to pay a Âč8m fine after admitting it participated in anti-competitive practices. A probe by NHS in the UK found that Aspen broke competition law by agreeing in 2016 to pay rival pharmaceutical firms to keep them out of the market, which gave the firm the opportunity to increase prices of one its products by up to 1,800 per cent.

MTN Group Ltd

21 February 2019 –Ugandan authorities announce probe into MTN Uganda following allegations of under-declaring sales and evading taxes.

VBS Mutual Bank

13 April 2018 –South African Reserve Bank commissions a forensic investigation into VBS Mutual Bank after the curator flagged several related-party transactions and was unable to confirm the existence of R900million in deposits. The investigation found that almost R2billion was gratuitously paid to 53 individuals over a period of three years without any just or legal cause. Furthermore, executives manipulated banking systems by creating enormous fictitious deposits.

Nenegate

10 December 2015 –On the evening of 9 December 2015, The Minister of Finance, Mr Nhlanhla Nene, was unceremoniously removed from his post. When markets opened the next morning, bond yields increased significantly and the currency depreciated. Risk perceptions that the South African government's commitment to fiscal sustainability was weakening were further reinforced by other political choices that followed. Markets reacted negatively to the appointment of a replacement; the currency depreciated by approximate 5% against the dollar in a single day. In a matter of days, another official was appointed to this position in a attempt to restore confidence in the market.

State Capture

02 November 2016 –Office of the Public Protector releases a report on an investigation into alleged improper and unethical conduct by the President and other state functionaries. The report relates to allegations of improper relationships and involvement of certain individuals in the removal and appointment of Ministers and Directors of State-Owned Enterprises, resulting in improper and possibly corrupt award of state contracts.

B.3 Rand-hedges

Table B.1. Rand-hedge stocks

Company	Ticker	Rand hedge qualities
AB InBev	ANH	Large foreign operations; USD reporting currency
Anglo American	AGL	USD price of metals has significant effect on earnings; Multinational operations; USD reporting currency
AngloGold Ashanti	ANG	Multinational operations; revenues are generated by gold sales denominated in USD; USD reporting currency
Aspen Pharmacare	APN	Approximately 80% of revenues generated in territories outside of South Africa.
Bid Corporation	BID	Large foreign operations across five continents.
BHP Billiton	BHP	USD price of metals has significant effect on earnings; Multinational operations; USD reporting currency
British American Tobacco	BTI	Revenues generated in multiple currencies; GBP reporting currency
Capital & Counties Properties	CCO	UK property holdings primarily valued in GBP.
Glencore	GLN	Multinational operations; USD reporting currency
Hammerson	HMN	UK property holdings primarily valued in GBP.
Intu Properties	ITU	UK property holdings primarily valued in GBP.
Mediclinic International	MEI	Group earnings and payment of dividends are presented and declared in GBP
MTN	MTN	transactions in numerous currencies recorded in USD before ZAR conversion.
Mondi	MNP	Multinational operations; EUR reporting currency
Naspers	NPN	Revenues generated in multiple currencies; USD reporting currency
New Europe Property Investments	NEP	Operations limited to European Union markets; EUR reporting currency.
Reinet Investments	RNI	EUR reporting currency.
Richemont	CFR	Sales primarily generated outside EMEA region ; EUR reporting currency.
SAB Miller	SAB	USD reporting currency
Sasol	SOL	Significant portion of revenues generated in USD
South 32	S32	Australia based; Multinational operations; USD reporting currency
Steinhoff International Holdings	SNH	Multinational holding company; EUR reporting currency

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