

STOCK PRICE CRASH RISK AND INSIDER TRADING: EVIDENCE FROM CHINA

BY

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Abstract

This paper examines the impact of prior crash risk on insider trading behaviour using a sample of Chinese A-share firms for the 2010-2015 period. Prior crash risk is publicly available information yet represents a source of informational advantage for insiders due to their unique capacity to assess its impact on stock price. Consistent with this assertion, we find a positive correlation between prior crash risk and insider sales value scaled by firm value. This result is robust to market sentiment and contrarian strategy. The result still holds after accounting for possible endogeneity issues using a two-stage least squares estimation. Additionally, we find the relationship is attenuated in state-owned enterprises (SOEs), where corporate governance affects insider motivation and creates administrative restrictions. Our study contributes to the growing literature on crash risk consequences by examining its association with insider trading behaviour. Our results are economically meaningful and feature important implications for investors, boards of directors, and policymakers.

Key words: stock price crash risk; insider trading; corporate governance; state-owned enterprises; Chinese A-share market

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1. Introduction

It is commonly accepted that insiders within a firm know more than outsiders. The opportunity for insiders to abuse this information advantage presents itself through insider trading, where insiders can buy (sell) under- (over-) valued shares based on information about impending firm-specific news. The Enron scandal represents one of the most well-known examples of willful corporate abuse. Executives used off-balance Special Purpose Vehicles to hide assets that were losing money. Meanwhile they informed the investing public that stock prices would continue to rise while secretly unloading their own shares. Between August 2000 and August 2001, share prices had fallen from \$90 to \$42 as analysts began to question whether Enron stock was overvalued. By December 2001, share prices plummeted to less than \$1 and shareholders filed a \$40 billion lawsuit. Twenty-one people were found guilty and convicted for a number of crimes including bank fraud, securities fraud, wire fraud, conspiracy, and insider trading. Executives at Enron enjoyed windfall gains of nearly \$900 million through illegal insider trading. The Enron case remains one of the most significant examples highlighting the extent and impact of stock price crash – \$74 billion of shareholder value evaporated, 4500 employees lost their jobs and life savings, and social trust in capital markets was shattered. This event triggered the enactment of the Sarbanes-Oxley Act, which requires top managers to certify financial statement accuracy and increases the severity of penalties for fraudulent activity, with the aim of decreasing information asymmetry between insiders and external investors. Other well-known companies like Nortel and Zynga suffered similar stock price crashes that heavily influenced insider trading behaviour.

Numerous studies demonstrate a significant and positive link between crash risk and information asymmetry, and the resulting impact that this asymmetry has on firms and the

market as a whole (eg. Hutton, Marcus, & Tehranian, 2009; Kim, Li, & Zhang, 2011a). The majority of the research on crash risk focuses on its determinants such as religion (Callen & Fang, 2015), social trust (Li, Wang, & Wang, 2017), and equity incentives (Kim et al., 2011a). My study focuses on the effect of crash risk on insider trading behaviour. Insider trading plays an important role in the financial market, though its ethical aspects are a grey area for many investors. Prior studies have examined insider trading through the lens of legitimacy, information efficiency, and ethics, and offer compelling arguments for and against unregulated insider trading (see Meulbroek, 1992; McGee, 2008). The term “insider trading” is subject to many definitions and connotations, and encompasses both legal and illegal activity. Legal insider trading occurs every day when corporate insiders – officers, directors, or employees – buy or sell stock in their own companies within the confines of company policy and government regulations (Newkirk & Robertson, 1998). Transactions are illegal when based on non-public and material information. Information is considered public if it is available to analysts following a firm. Information is considered material if it can impact share price. China defines material information in Article 75 of the Securities of the People’s Republic of China as “information that concerns the business or finance of a company or may have a major effect on the market price of the securities” (Securities Law, 2018). In contrast to the United States, the news regarding insider trading in China is scarce, despite its purported rampancy (Cheng, 2008). Due to the nature of China’s legal environment and the relative inefficiency of the Chinese Securities Regulatory Commission (CSRC), insiders are rarely prosecuted without significant political backing. Only recently has China embarked on an anti-corruption campaign targeting its financial sector with its high-profile arrest of Xu Xiang in January 2017, later convicted of insider trading and sentenced to 5 years in prison and fined 11 billion yuan (US \$1.6 billion).

My study focuses on how prior crash risk – a publicly available source of information - affects insider trading behaviour. Despite being publicly available, prior crash risk may not be adequately captured in share price due to its abstract nature. Therefore, it presents a source of potential information advantage for insiders who are better able to assess their firm's intrinsic value. Due to the cost of collecting information, the public will often have less access to information, and their information will be less accurate and timely. Inversely, insiders possess a greater access to information owing to their proximity to business decisions. This access may come from a variety of sources such as knowledge of an impending IPO, company leverage, or earnings. I follow Jin and Myer's (2006) bad news hoarding theory of crash risk, which states that managers will hold on to bad news in order to receive private benefits up until the point where the costs of withholding the bad news are greater than the benefits they enjoy. At this point, they release the bad news all at once and the accumulated impact causes stock price to crash. In opaque environments, the bad news is easier for managers to hide, which increases the firm's crash risk. Meanwhile, firm crash risk also affects how an insider will trade their own shares, opting to potentially buy (sell) shares when firm crash risk is low (high). Owing to the transparent nature of these relationships, insiders must consider the legal and corporate responses to their trading behaviour. Prior research has shown that insiders avoid ex ante transactions due to the increased regulatory scrutiny and legal sanctions associated with such transactions (Noe, 1999; Huddart, Ke, & Shi, 2007; Kallunki, Nilsson, & Hellström, 2009). Insiders weigh the perceived financial benefits of a transaction against the potential costs of enforcement and litigation.

Although empirical literature has argued for the firm-specific benefits of insider trading, regulators often blame insider trading for inducing excessive managerial risk taking. Excessive

risk taking behaviour does not necessarily create crash risk, as undesired high levels of managerial risk-taking can be managed by rational investors and the board of directors (Kim et al., 2011a). However, when managers withhold information, uninformed investors and boards are not able to take timely corrective action or adjust price levels until a crash occurs. Managers are incentivized to withhold information as this creates scenarios where they can benefit from an information advantage. Since information asymmetry contributes to crash risk, an information-motivated insider transaction will negatively impact a firm and its investors.

The relevant literature, with the exception of Jin and Myers (2006), uses U.S. data. I use instead a database on the emerging Chinese A-share market to examine several hypotheses. A detailed study using the Chinese stock market will allow me to shed light on insider behaviour in an emerging market and the findings could be useful to investors and regulators in China and other emerging markets in terms of understanding how prior crash risk relates to insider decision making. China's securities market presents a unique landscape for the study of crash risk and insider trading. First, unlike in the U.S., Chinese stock exchanges use price-limit rules that help to reduce crash risk. The 10% limit on daily price fluctuations serves as a market stabilization tool and reduces large price movements. The empirical and theoretical evidence regarding the efficacy of price-limit rules is controversial, though Deb, Kalev, and Marisetty (2010) explain that daily price-limit rules increase monitoring efficiency in environments prone to price manipulations. Second, insider trading in China's A-share market is a relatively new phenomenon – prior to market reform in 2007, insiders were not allowed to trade their shares. Third, stock trading in China is primarily composed of retail investors, who account for over 80% of total trading volume (CSRC, 2017). Recent New York Stock Exchange (NYSE) data reveals that retail investors represent less than 2% of NYSE trading volume and that the

remainder is composed of institutional investors (Evans, 2006). Institutional investors are significantly better at acquiring firm-specific information which serves to reduce insider information advantage. Fourth, corporate governance in Chinese firms differ greatly from their U.S. counterparts. Ownership in China is highly concentrated into single families or the government, while U.S. firm ownership is much more dispersed. While state-owned enterprises (SOEs) like Fannie Mae and Freddie Mac exist in the U.S., they are rather unique compared to the abundance of SOEs in China. SOEs differ from traditional public companies as the government appoints managers and profit is often not the primary objective. Finally, the regulatory and legal environment in China is immature in comparison to the United States. Systems designed to monitor insider trading are ineffective as financial reports lack both transparency and timeliness. Similarly, enforcements against insider trading are subject to politics rather than law. In the U.S., victims of illegal insider trading may pursue civil action in addition to a federal investigation. In China, there is no legal recourse for victims and courts rarely convict insider trading.

For my empirical analysis, following Chen, Hong, and Stein (2001) and Xu, Jiang, Chan, and Yi (2013), I use the negative coefficient of skewness (*NCSKEW*), down-to-up volatility (*DUVOL*), and daily returns severely below the mean (*COUNT*) to measure crash risk. For my insider trading variables, I modify Huddart and Ke's (2007) measures to construct an individual insider sales measure scaled by firm size (*SALES VP*) and aggregate measures based on firm-year and firm-half-year. Using a sample of 4134 individual insider transactions, my findings suggest that insiders in China use publicly available crash risk information to make more informed trading decisions than external investors. I find that a firm's increase in prior crash risk leads to an increase in insider sales value and this positive relation is attenuated in SOEs. In

contrast, I find little evidence that prior crash risk affects aggregate firm insider trading. My results are robust to alternative variable measures and different regression model specifications.

My paper offers several contributions to the literature. First, I examine the impact of crash risk on insider transaction value. Prior research has examined crash risk as a dependent variable, but its use as an explanatory variable allows me to draw conclusions about its relative value in explaining insider decisions compared to other variables commonly used in the literature. Understanding how an insider reacts to crash risk is crucial for firms seeking to mitigate future crash risk and protect shareholder value. Xing, Zhang, and Zhao (2010) and Yan (2011) both suggest that extreme distributions of stock returns have a major effect on investor welfare. Therefore, my study is valuable in understanding the role that insider trading plays in influencing both corporate behaviour and investor welfare. Second, most studies focus on developed markets, especially the U.S., and provide limited insight into developing markets with different legal and corporate environments. My study complements previous studies by observing an emerging market. Third, I examine how corporate governance in a developing market affects trading decisions. Specifically, I study how ultimate shareholder status in a firm affects the crash risk – insider trading relationship. A greater understanding of the effects of corporate governance helps promote efforts in the development of more stringent control measures for managing undesirable insider behaviour.

The remainder of the paper is structured as follows. [Section 2](#) conducts a review of the related literature. [Section 3](#) explores my hypothesis development. [Section 4](#) describes the data and the measurement of key variables. [Section 5](#) contains my empirical analysis and [section 6](#) contains my conclusion and limitations.

2. Literature Review

2.1 *Crash Risk*

Crash risk is the probability of a firm-specific crash, conceptually understood as extreme negative values in the distribution of returns after controlling for co-movement factors (Kim, Li, & Zhang, 2011b; Kim et al., 2011a). Jin and Myers (2006) provide the theoretical framework for the bad news hoarding theory of crash risk, arguing that information asymmetries between managers and shareholders contribute to crash risk. The theory suggests that managers hoard bad news in order to extract benefits from the firm, such as continued employment, excess perks (Xu, Li, Yuan, & Chan, 2014), equity incentives (Kim et al., 2011b), and reputation (Ball, Jayaraman, & Shivakumar, 2009). Managers bear a cost for withholding bad news by making up the difference between the firm's actual performance and investors' estimate of that performance; this cost is lower in opaque information environments and correspondingly, managers are able to withhold relatively more bad news. When this cost reaches a certain threshold, managers choose to release the accumulated bad news, resulting in a stock price crash – a large negative outlier in the distribution of returns. Consistent with the bad news theory, a survey by Graham, Harvey, and Rajgopal (2005) finds that managers possessing bad news tend to delay disclosure more than those with good news. Kothari, Li, and Short (2009), in their study on dividend changes and earnings forecasts, provide similar evidence demonstrating that managers delay the release of bad news to investors. Hutton et al. (2009) and Kim et al. (2011a) quantitatively support the bad news hoarding theory by providing evidence of a significant, positive relationship between crash risk and extreme information asymmetry.

The current crash risk landscape is heavily focused on the determinants of firm-specific crash risk, but there is a paucity of research on the consequences of crash risk. This is rather

surprising given how crucial it is to understand how firms and regulators respond in order to mitigate future crash risk and protect shareholder value. To the best of my knowledge, only two papers examine how firm-specific crash risk affects firm operations. An, Li, and Yu (2015) examine how crash risk affects speed of leverage adjustment and how this effect is moderated by the information environment. Using data from 41 countries from 1989 to 2013, they show that firms with a higher crash risk more slowly adjust their financial leverages towards targets. They also show that the negative relationship between crash risk and speed of leverage adjustment is less pronounced for firms in countries with more transparent financial reporting environments. Hackenbrack, Jenkins, and Pevzner (2014) demonstrate a 2% increase in clients' audit fees ahead of a price crash occurrence. They employ crash risk as a proxy for auditors' perception of idiosyncratic risk and their findings suggest that this is a significant driver in audit fee increases.

2.2 *Insider trading*

While official definitions differ according to country-specific regulations, an insider is generally defined as an executive, director, or senior officer of a company or an entity that owns a certain percentage of a company's voting shares. In China, any shareholder holding more than 5% of a company's stock is considered a large shareholder and categorized as an insider. Insiders may possess an information advantage in different ways. For example, insiders know which events will impact stock price, can better assess growth potential and earnings prospects, and have a better understanding of their company's intrinsic value such that they can exploit situations when the market over- or undervalues the company. Previous studies based on U.S. data unanimously show that insiders are better informed and earn abnormal returns (eg. Jaffe, 1974; Finnerty, 1976; Rozeff & Zaman, 1988; Seyhun, 2000). As Seyhun (2000) noted, if you want to find smart investors, these are the smart investors.

The majority of media coverage surrounding insider trading makes it appear as though the activity is illegal, though this is not true. When an insider has an information advantage over outside investors, there is information asymmetry. Information asymmetry between insiders and outside investors is a fundamental issue – its reduction has long been a goal for Chinese regulators to advance the cause of an efficient and transparent market. Significant empirical research has been dedicated to measuring insider information advantage and the informational content of transactions. Easley and O’Hara (1992) expand on Kyle’s (1985) model of imperfect competition and insider trading strategy by demonstrating that no-trade can serve as a signal to the market maker that there is no new information, prompting a reduction in the bid-ask spread. More importantly, Easley and O’Hara (1992) demonstrate that time between trades affects spreads and that an absence of trades is correlated with volume. In following works (eg. Easley et al, 1996a, b; 1997a, b; Easley et al. 2008), the concept and empirics of the probability of informed trading (PIN) is introduced and solidified. This variable is formed from a Bayesian market maker perspective as an econometric measure that follows a probabilistic decision tree structure to determine bid-ask spreads. Signals throughout a trading period cause spread adjustments.

My study examines prior crash risk – a source of information that is publicly available and has the potential to impact share price. Intuitively, *ceteris paribus*, a firm with higher crash risk is a less desirable investment option than one with low crash risk. Given the evidence that Chinese insiders can better assess public information and often trade against the market (Zhu, Wang, & Yang, 2014), I believe that insiders can similarly assess and utilize publicly available crash risk information more effectively than outside investors. Though it may seem intuitive that insiders possess an information advantage and that their trades are necessarily conditioned on

this advantage, it is sometimes difficult to prove this fact (Beneish & Vargus, 2002). While the impact of an insider trade - especially a large one - is noticeable, systems in place to monitor insider behaviour may not be effective in determining and corroborating an insider's motive. In particular, insider sales are less informative, less profitable, and more frequent than insider purchases (Jeng, Metrick, & Zeckhauser, 2003). While insider purchases signal optimism about the firm, sales may be conducted for a number of reasons that preclude the use of private information, such as tax benefits (Shefrin & Statman, 1985), need for liquidity, or diversification (Lakonishok & Lee, 2001). Ofek and Yermack (2000) demonstrate that executives tend to sell existing stock when they receive new grants and options, providing empirical evidence to support the notion that sales may be driven by a desire to maintain a balanced portfolio.

The decision to engage in insider trading is not taken lightly for fear that a legal trade may be perceived to be based on private information. Kallunki et al. (2009) find that insiders typically avoid selling before bad news earnings announcements to avoid regulatory scrutiny. Similarly, Noe (1999) and Huddart et al. (2007) report that insider trading activity increases (decreases) after (before) firm earnings are published as legal sanctions are greater for transactions that occur ex ante. Applying Becker's (1968) economics of crime approach to illegal insider trading, Thevenot (2012) finds that insiders weigh the perceived financial benefits of a transaction against the potential costs of SEC enforcement and private litigation.

Gunny, Ke, and Zhang (2008) demonstrate that insider trading behavior is systematically affected by corporate governance through ownership structure. This affects power and information distribution and internal monitoring behaviour, which in turn affects insider motives. Dai, Fu, Kang, and Lee (2016) find that corporate governance significantly reduces the profitability of insider sales but not purchases. This suggests that well-governed firms reduce

insider sales profitability due to the greater legal risk of sales transactions. Furthermore, they find that well-governed firms are more likely to introduce ex-ante preventative measures, implement such measures more effectively, and are more active in ex-post disciplinary actions.

There is no consensus on the expected sign for the relationship between the information content and the value of a transaction. Many authors expect a positive relationship as highly valuable information may motivate insiders to execute larger trades to maximize profit (eg. Easley & Ohara, 1987; Eckbo & Smith, 1998). Others provide evidence of a negative relationship, anticipating that it is easier to camouflage private information-based trades when they are smaller (Marshall, 1974). A study of U.S. insiders concludes that medium-sized trades are preferred when a transaction is based on private information (Garfinkel & Nimalendran, 2003).

2.3 *Causal Relationship*

There are two schools of thought regarding the relationship between crash risk and insider trading within Jin and Myers (2006) theory of bad news hoarding. The managerial disclosure incentives perspective explores how insider trading influences managerial incentives for bad news hoarding, which in turn affects stock price crash risk. This school of thought posits that managers have an incentive to hide bad news to create an early exit opportunity to maintain the value of their wealth. Hu, Kim, and Zhang (2014) explore the impact of the enactment and enforcement of insider trading regulations on crash risk across 48 countries. They find that enforcement rather than enactment imposes higher legal costs on insider trading activities, and that increasing the costs of insider trading reduces managerial incentives to hide bad news, decreasing crash risk. Their research reveals three moderating factors: (1) investor protection; (2) information environment; and (3) corporate governance. First, prior research has demonstrated

that firms in countries with weaker legal enforcements are more likely to accumulate bad news over time, and thus have a greater tendency to experience crashes (Kim et al., 2011b). Stronger insider trading law enforcement limits the benefits associated with insider information advantage and protects outside investor rights. Second, previous studies show that information opaqueness and poor financial reporting quality lead to higher crash risk ((Jin & Myers, 2006; Hutton et al., 2009). Insider trading acts as a disincentive for outside investors to acquire private information about the firm (Fishman & Hagerty, 1992) and incentivizes insiders to supply low-quality information so that greater benefits can be expropriated (Bergstresser & Philippon, 2006). Greater enforcement of insider trading laws improves the information environment and lowers crash risk. Third, existing research finds that weak corporate governance facilitates insiders' rent-seeking behaviours, such as engaging in inefficient investments or hiding the bad performance of projects until its eventual materialization, which increases crash risk (Bleck & Liu, 2007).

The second perspective predicts that insiders can anticipate a firm's crash risk and use this information when trading. This perspective is consistent with a vast literature documenting insiders' tendency to trade on knowledge of bad news including bankruptcy (Seyhun & Bradley, 1997), dividend announcements (John & Lang, 1991), disclosures of internal weaknesses (Skaife, Veenman, & Wangerin, 2013), SEC enforcement actions (Thevenot, 2012), announcements of accounting misstatements (Agrawal & Cooper, 2015), disclosures of negative SEC comment letters (Dechow, Lawrence, & Ryans, 2015), breaks in a series of consecutive increases in quarterly earnings (Ke, Huddart, & Petroni, 2003), and earnings disappointments (Darrough & Rangan, 2005). However, the major issue with this perspective is that the prior examples associate insider activity with a bad news event, which exists dichotomously as either

having occurred or not occurred. This is more aptly reflected by the effect of stock price crash on insider trading, rather than a firm's stock price crash *risk*. A potentially improved perspective on this causal relationship may posit that bad news hoarding increases firm crash risk, managers recognize the increased crash risk and its associated effect of overvaluing stock price, and then sell their stocks accordingly. This interpretation does not require a crash to occur for risk-averse managers to decrease their stock holdings. The immediate criticism of this interpretation is that insider sales can inform the market by acting as a bad news signal, which would lower crash risk and reverse the presupposed direction of causality. However, research on the information content of insider trades finds that sales are generally less informative due to the number of reasons that insiders may sell stock (Lakonishok & Lee, 2001). Therefore, an insider sale may not necessarily inform the market and relieve crash risk. Since unseen crash risk decreases the inherent value of the stock, insiders profit when the price eventually falls. In the event that the price does not crash, the insiders can simply return to their initial holding positions. In a conference paper, He, Ren, and Taffler (2016) find evidence that insider sales are positively associated with future stock price crash risk. This is consistent with the view that insiders are able to assess and anticipate future crash risk and exploit this information advantage to achieve personal trading objectives. They also find that this association is stronger in opaque firms and weaker in the post-SOX period.

Due to the contradictory research regarding the causality between crash risk and insider trades, I opt to employ prior year crash risk as my independent variable. This creates temporal causality and allows me to effectively study how crash risk affects insider trading. The use of prior crash risk is superior to future crash risk as it greatly decreases endogeneity concerns. In He et al.'s (2016) paper, insiders sell their shares in reaction to anticipated future stock price, with

time periods between sale and measured crash risk ranging from 12 to 39 months. The concern is that insiders are able to influence crash risk after their sales transactions: some insiders may seek to increase their own profits by actively engaging in negative net present value (NPV) projects (Bleck & Liu, 2007). The bad performance of negative NPV projects accumulates and eventually materializes, which increases crash risk

2.4 *Chinese Stock Market*

The majority of crash risk literature and insider trading literature have focused on the U.S. stock market. This study will be one of the first to examine the relationship between crash risk and insider trading in an emerging market. Emerging markets feature highly concentrated corporate ownership and weak legal institutions. Although emerging markets have introduced regulations and laws on insider trading, their enforcement is less effective than developed countries, with prosecution rates of only 25% (Bhattacharya & Daouk, 2002). Mexican firms demonstrate an extreme result of weak enforcement; Bhattacharya, Daouk, Jorgenson, and Kehr (2000) find that corporate news announcements have no impact on stock returns, volatility, trade volume, or bid-ask spreads as unrestricted insider trading causes prices to incorporate news content before its release.

China's A-share market has a number of unique features that make its study rewarding. Initially, the A-share market had tradable and non-tradable shares, where executives and large shareholders held mostly non-tradable shares. Market reform allowed stakeholders to trade their non-tradable shares, but the CSRC introduced lockup periods of one to three years to mitigate supply pressure. Since the beginning of 2007, locked up stocks have become gradually tradable. The CSRC enacted trading ban regulations on executives in April 2007 and on large shareholders in April 2008. Executives are prohibited from trading 10 days before an earnings

preannouncements and 30 days before the issuance of a formal financial report. Large shareholders with holdings over 30% cannot purchase shares 10 days before an earnings preannouncement or formal financial report, and are also banned from selling 30 days before semi-annual and annual financial reports. The CSRC regulates that insiders must disclose their trading to their firm, which then discloses this information to the CSRC. This information includes the volume and date of the trade, as well as the identity and stockholdings of the insider.

In comparison to developed markets that are mainly composed of institutional investors, China's stock market is dominated by retail investors, who account for over 80% of total trading volume (CSRC, 2017). Retail investors have relatively less expertise in collecting and interpreting information, giving insiders greater informational advantages, and thus a greater incentive to trade. Zhu et al. (2014) argue that Chinese analysts - acting as information intermediaries - have yet to mature, providing less insight to reduce information asymmetry. The role of corporate governance also plays a crucial role in Chinese insider trading activities. Firstly, ownership is highly concentrated into single families or government, providing the structure for insiders to take advantage of investors (He, Chong, Li, & Zhang, 2010). Secondly, corporate governance affects the motives of insiders to use their information advantage in trading; Zhu and Wang (2015) find non-SOE large shareholders engage in more profitable insider trading relative to large shareholders in state-owned enterprises due to different informational advantages, profit-seeking incentives, and risk preferences. The largest shareholders in non-SOEs have highly concentrated or controlling ownership stakes due to weak investor protection in the A-share market. These shareholders are more active in business operations and have strong incentives to monitor managers, resulting in an alignment of interests where both parties can benefit from the use of private information. Contrast this to state-owned enterprises where the state delegates

bureaucrats, often resulting in poor corporate governance. Since SOE large shareholders rarely participate in business operations, they possess little information advantage. Furthermore, Zhu et al. (2014) identify executive status as an indicator of insider trading behavior, finding that state-owned enterprises that are centrally owned in strategically important industries have executives who possess “quasi-official” status which allows opportunities for promotion to the provincial or ministerial government levels. Promotion is partially based on character and integrity, so promotion-track executives are incentivized to avoid profitable insider trading.

China’s legal framework is poorly equipped to monitor insider trading. Allen, Qian, and Qian (2005) find that China’s information disclosure and enforcement system is weak compared to developed markets and poor relative to India and Brazil. Ball, Robin, and Wu (2000) document that Chinese listed firms lack timely incorporation of economic losses in their accounting reports, which they attribute to managers’ and auditors’ low incentive to recognize losses in a timely fashion, and the high political and tax influences on financial reporting practices. Similarly, Bushman, Piotroski, and Smith (2004) find that financial transparency is lower in countries with a high share of state-owned enterprises and in countries where firms are more likely to be harmed by revealing sensitive information to competitors or local governments. In addition to ineffective monitoring, China also suffers from ineffective enforcement. Weng (2014) argues that Article 74’s definition of an insider allows the CSRC unbridled power in over- and under-prosecuting individuals, subject to political and public opinion. Secondly, the CSRC has two objectives that sometimes conflict. The CSRC is responsible for enforcing regulations to protect investors and market integrity, and also has a political duty to protect state assets and spread state policy (Shen, 2009). Conflicts arise when enforcement actions may negatively impact state assets. Thirdly, China has insufficient resources to enforce insider trading

regulations (Duan, 2009). Enforcement is reliant on the CSRC's administrative actions as the legal system offers little protection against insider expropriations (Berkman, Cole, & Fu, 2010). Lastly, the CSRC has limited power in terms of barring illegal insiders from attaining new director or officer positions. In general, neither the People's Procuratorates nor the People's Court find insider trading to be a serious crime. Cases have only been prosecuted when connected to bribery and corruption charges (Cheng, 2008). China's opaque disclosure environment and weak law enforcement significantly reduce the cost for insiders to trade on private information.

China's securities market employs a price-limit designed to reduce crash risk. The Shanghai Stock Exchange (SSE) implements a 10% limit on daily price fluctuation for stocks, with a 5% limit for special treatment stocks (SSE, 2017). These rules are popular in emerging markets with a large fraction of retail investors as they enable a time-out period during large price movements and serve as a market stabilization mechanism. Using a game-theoretic framework, Deb et al. (2010) provide an explanation for why regulators use daily price-limit rules even though many empirical and theoretical studies criticize their usefulness: in a market prone to price manipulations and characterized by high monitoring costs, price-limit rules increase monitoring efficiency. The imposition of these rules is positively associated with countries that incur higher monitoring costs due to poorer business disclosure, higher corruption levels, and lower efficiency in the legal, regulatory, and technological environments.

3. Hypothesis Development

There is a plethora of evidence to suggest that insiders trade on bad news. For example, prior studies have examined how insiders react to bankruptcies (Seyhun & Bradley, 1997), SEC enforcement actions (Thevenot, 2012), breaks in a series of consecutive increases in quarterly

earnings (Ke et al., 2003), and earnings disappointments (Darrough & Rangan, 2005). Prior research provides an inconsistent expected relationship between trade value and insider information. Highly valuable information may motivate larger trades that maximize profit, but larger trades naturally attract more regulatory attention and increase an insider's legal jeopardy. Pursuant with the logic that insiders view prior crash risk as bad news, I anticipate a positive relationship between prior period crash risk and insider sales value. Seyhun (2000) demonstrates that sales value increases with firm size so I divide the value of the trade with the market value of the firm to obtain sales value percentage.

Hypothesis 1A: Insider sales value percentage is positively associated with prior year crash risk.

An alternative argument can be made that an insider may believe that a stock price has reached its minimum level during a crash and will begin to rise. In this scenario, an insider will purchase additional shares or hold on to existing shares following a period of crash risk and the expected relationship between prior year crash risk and sales value percentage is negative. To explore this relationship further, I subsample my crash risk measures into "high" and "low" groups based on median crash risk. For the high crash risk group, I anticipate that insiders will be more likely to sell shares as the risk of further stock price crash does not justify buying or holding. Inversely, I anticipate insiders will be more likely to hold on to existing shares when crash risk is low in order to capitalize on a perceived undervalued stock.

Hypothesis 1B: The relationship between insider sales value percentage and prior year crash risk is stronger in the high crash risk groups and weaker in the low crash risk groups.

A complete examination of the relationship between insider trading and prior crash risk requires that stock purchases also be assessed. An analysis that considers value conditional on a sale may overstate sales value. To address this issue, I aggregate insider trade value at the firm-

year level. Prior research documents insiders as contrarian traders (eg. Seyhun, 1992; Jenter, 2005; Piotroski & Roulstone, 2005). Insiders using this strategy tend to trade against prevailing market trends by purchasing stocks when they are performing poorly and selling them when their performance improves. Averaging the actions of sufficiently many managers provides a more valid signal about insider trading decisions (Baker & Wurgler, 2000), whereas individual beliefs about misvaluation may be determined by hierarchical access to observable information. Since sales are still the transaction of interest, I measure net insider sales as total sale value minus total purchase value on a firm-year level and anticipate that an increase in prior crash risk leads to an overall increase in current net sales value.

Hypothesis 2: Net insider sales value is positively associated with prior year crash risk.

Corporate governance has a systematic effect on insider trading behaviour (Gunny et al., 2008). Firstly, ownership structure affects the distribution of control between shareholders and executives, which affects information advantage for specific insiders. Secondly, different corporate governance structures monitor insider behaviour differently, which affects an insider's motive and likelihood to use their information advantage in trading. Zhu et al. (2014) find that insider transactions in non-SOEs are more predictive of market returns than insider transactions in SOEs due to different profit motivations and a greater involvement in business operations. Additionally, the monitoring effect of large shareholders in non-SOEs is mitigated by an alignment of incentives between large shareholders and managers. Furthermore, non-SOE insiders face less regulatory scrutiny than SOE insiders. Due to this hidden but strong administrative control, executives in SOEs are less motivated to use information to trade profitably. These factors indicate that insiders within an SOE observe unique restrictions and motivations, and are less likely to be influenced by prior crash risk when trading their shares.

Hypothesis 3: The relationship between insider sales value percentage and prior crash risk is less pronounced in state-owned enterprises.

4. Data and Methodology

4.1 Data

All purchase and sale transactions analyzed in this study are taken from the Chinese Stock Market and Accounting Research (CSMAR) database. These records include stock code, name and position of insider, trade date, shareholding volume before and after trade, number of shares traded, average trading price, and reason for trade. My analysis covers all disclosed A-share insider trades from listed firms on the Shanghai Stock Exchange from April 1st, 2010 to March 31st, 2015, corresponding with Chinese fiscal year 2010 to 2015. I begin my analysis from 2010 to allow a three year gap from the 2007 market reform legalizing insider trading, in order to limit large-scale diversification sales. The CSMAR database also includes shareholder equity structure, which allows me to calculate my value percentage variable.

Following Pettit and Venkatesh (1995), I exclude individual transactions exceeding \$1000,000USD (or ¥6,670,000) as they often have different motivations than the trades I am concerned with and sometimes serve as informational events themselves. These trades are eliminated to maintain reasonable homogeneity in the trades analyzed. I also eliminate trades lacking sufficient information to calculate my dependent variables. In total, I eliminate 961 trades (363 for large trade value, 598 for lacking information) or 18.5% of my initial sample. Summary statistics on the number and value of all insider transactions are given in Table 1. In total, there are for 4134 transactions across the five year sample period, of which 1911 are purchase transactions and 2223 are sales transactions. Market value is measured as the A-share value of equity in the month of the insider transaction. The 338 SSE-listed firms I study over the

60 month period feature an average individual sale value of ¥1,042,147 and an average firm-year net sales value of ¥4,880,507.

I collect my crash risk data from the CSMAR database which provides daily stock returns, industry information, and financial statements. Modifying the guidelines from Xu et al. (2013), which relies on weekly stock return data, I exclude (1) firms with fewer than 150 days of stock return data, (2) non-A-share stocks, (3) financial services firms, and (4) firm-year observations with insufficient financial data to calculate control variables.

I collect my shareholder data from CSMAR and categorize firms as state-owned enterprises when the ultimate controlling shareholder is the state. For all other firms, I classify them as non-SOEs.

Table 1: Summary Statistics of Individual Insider Transactions

Sale and purchase transactions are separated. Market value is measured in the month of the insider transaction and is reported in units of CNY 1000. All transactions exceeding ¥6,670,000 have been excluded. *Negative values in the volume and trade value rows correspond with sales transactions. On average, the value of an individual sale exceeds that of a purchase. This relationship is inversed for volume, indicating that more shares were purchased than sold during my sample period. This indicates that insiders tend to sell shares when price is relatively high and purchase shares when price is relatively low.

	<i>Min.</i>	<i>Max.</i>	<i>Mean</i>	<i>Median</i>	<i>SD</i>
Sales volume	10	1,800,000	85,184	33,000	136,050
Purchase volume	91	1,850	116.473	33,000	204,100
Volume*	-1,800,000	1,850,000	7,914	-2,250	198,240
Number of shares	25,740	69,920,000	1,303,000	563,200	3,072,427
Price	1.58	73.87	13.20	11.25	8.83

Sales value	169	6,617,956	1,042,147	495,300	1,338,180
Purchase value	584	6,598,800	797,924	298.662	1,165,660
Trade value	-6,617,956	6,598,800	-192,645	-32,100	1,559,690
Market value	291,377	571,962,285	11,437,954	6,450,439	17,630

4.2 *Insider Trading Variables*

4.2.1 *Sales Value Percentage*

Trade value is trade volume multiplied by stock price. Transactions are subset into sales and purchases, since sales transactions are my variable of interest. I define value as the renminbi value in thousands. I calculate trade value percentage by dividing trade value by firm market value in the most recent monthly period. My constructed variable is *SALES VP*, which reports the size of an individual transaction as a percentage of total market value. I report an absolute value for *SALES VP* so an increase in the variable corresponds with an increase in sales value as a percentage of total market value. *SALES VP* is similar to the trade value variable used by Huddart and Ke (2007), though they report a transformed trade value while I scale trade value with respect to firm size. Scaling with firm size allows me to control the effects of large trades driven by a large number of outstanding firm shares. This scaling is different from the *STOCKHOLDING* control variable discussed later on, which only controls for specific insider share holdings rather than firm size. Alternatively, firm size can be controlled for by implementing a firm size control variable.

4.2.2 *Net Sales Value*

Prior literature has used aggregate insider trading measures extensively as a comprehensive firm-level indicator (eg. Lakonishok & Lee, 2001; Huddart & Ke, 2007; Zhu et

al., 2014). My aggregate measure follows Huddart and Ke (2007) by using trade value rather than trade volume. Aggregated trade value allows me to incorporate price into my model as price movements are a significant determinant in both insider trading decisions and crash risk. Net sales value is aggregated on a firm-year level as the difference between sales and purchases. My sample consists of 588 firm-years with 329 net sale firm-years, 256 net purchase firm-years, and three net zero firm-years. I also aggregate net sales for six-month periods (*NETSALE6*) and refer to them as firm-half-years. The half-year periods are measured from April 1 to September 31 and October 1 to March 31. This sample consists of 722 observations with 430 net sale firm half years, 290 net purchase firm half years, and two net zero firm half years. Table 2 reports the summary statistics of my dependent variables.

4.2.3 Probability of Informed Trading

There are a number of insider trading measures found in the literature that were not employed, including net purchase ratio (NPR), profitability, and information content. None of these measures are especially appropriate as a dependent variable when the predictor variable is stock price crash risk. Two mechanisms are crucial for my dependent variable: firstly, it must be able to measure *individual* insider transactions; secondly, it must capture insider sales since sales are the theoretically anticipated response to increased crash risk. With this in mind, NPR is precluded since it only measures net insider activity. For Hypothesis 2, I opt to use a net insider measure that is a simple aggregate of individual activity in lieu of NPR since introducing a ratio would add an unnecessary operator. I do not measure profitability since I do not have access to the data necessary to calculate abnormal and expected returns. PIN is one measure of information content found in insider literature. I do not use PIN or information content since they are not the variable of interest for this research. My focus is on how insiders change their selling

activities, not the amount of private information contained in an insider transaction. Since prior year stock price crash risk is publicly available information, the use of information content as a dependent variable seems paradoxical.

4.3 *Crash Risk Variables*

Prior literature examining crash risk calculates non-overlapping six month or twelve month measures by using firm-specific daily or weekly returns (eg. Xu et al., 2013; Callen & Fang, 2015). Chen et al. (2001) find that more frequent measurement periods lead to greater measurement error due to the strong influence of outliers on skewness. My study differs from extant research since I employ crash risk as an explanatory variable. Thus, I calculate overlapping month-specific crash risk measures based on twelve-month measurement periods. This approach yields a crash risk measure per month of study, which allows me to more accurately interpret the relationship between crash risk and the insider trading variables.

I construct three measures of crash risk following Chen et al. (2001) and Xu et al. (2013). First, I estimate firm-specific daily returns, denoted by D , as the natural log of one plus the residual return from the expanded market model regression for each firm and year:

$$r_{i,t} = a + B_1 r_{m,t-2} + B_2 r_{m,t-1} + B_3 r_{m,t} + B_4 r_{m,t+1} + B_5 r_{m,t+2} + \varepsilon_{i,t} \quad (1)$$

where $r_{i,t}$ is the return on stock i in day t and $r_{m,t}$ is the value-weighted A-share market return for day t . Following Dimson (1979), I correct for non-synchronous trading by including lead and lag terms for the market index. The firm-specific daily returns for firm i on day t are represented by $D_{i,t} = \ln(1 + \varepsilon_{i,t})$ where $\varepsilon_{i,t}$ is the residual in Eq. (1).

4.3.1 *COUNT*

The first crash risk measure, *COUNT*, is the difference between the number of firm-specific daily returns exceeding 3.09 standard deviations below and above the mean firm-

specific return over the fiscal year, with 3.09 chosen to generate frequencies of 0.1% in the normal distribution (Hutton et al., 2009). *COUNT* is downside frequencies minus upside frequencies – a higher value of *COUNT* corresponds to a higher frequency of crashes.

4.3.2 *NCSKEW*

The second measure of crash risk is the negative conditional skewness of firm-specific daily returns over the fiscal year (*NCSKEW*). *NCSKEW* is computed as the negative third moment of each stock's firm-specific returns, divided by the cubed standard deviation.

Specifically, for each firm i in year t , I calculate *NCSKEW* as:

$$NCSKEW_{i,t} = \frac{-\left(n(n-1)^{\frac{3}{2}} \sum R_{i,t}^3\right)}{\left((n-1)(n-2) \sum R_{i,t}^2\right)} \quad (2)$$

where n is the number of observations of firm-specific daily returns and $R_{i,t}$ represents the sequence of de-meaned daily returns. The denominator is a normalization factor (Greene, 2008). Generally, *NCSKEW* data does not use any firm that has more than five missing observations. *NCSKEW* uses a negative sign in front of the third moment for simpler interpretation (Chen et al., 2001) - an increase in *NCSKEW* equates to a greater risk of crash.

4.3.3 *DUVOL*

The third measure of crash risk is the down-to-up volatility measure (*DUVOL*) of return asymmetries, which does not use third moments and is thus less likely to be influenced by extremely negative returns (Chen et al., 2001). *DUVOL* is computed by separating all days as returns below the fiscal year mean ("down" days) and above the fiscal year mean ("up" days). The standard deviation of daily returns is calculated for each of these subsamples. *DUVOL* is the natural log of the ratio of the standard deviation in the "down" days to the standard deviation of the "up" days. Thus I have:

$$DUVOL_{i,t} = \log \frac{(n_u-1)\sum_{down} R_{i,t}^2}{(n_d-1)\sum_{up} R_{i,t}^2} \quad (3)$$

where n_u is the number of “up” days and n_d is the number of “down” days. A higher value of *DUVOL* indicates greater crash risk.

Among the three measures, *COUNT* is the most direct measure of firm crash risk and is used most frequently in the crash risk literature. *NCSKEW* and *DUVOL* are valuable because *COUNT* cannot capture stock price crashes in scenarios where a firm gradually releases bad news such that stock price declines consistently and plateaus. In said circumstance, the stock price would still exhibit negative conditional return skewness and high down-to-up volatility. Table 2 reports the summary statistics for the crash risk measures, calculated from daily stock return data and based on twelve-month measurement periods.

Kim and Zhang (2014) introduced the option implied volatility smirk as a proxy for crash risk. The smirk refers to when the same underlying instrument has a higher implied volatility for out-of-the-money (OTM) puts than for at-the-money (ATM) calls. Logically, traders require greater premiums for higher implied volatility due to the increased crash risk of OTM puts. Kim and Zhang (2014) measure implied volatility skew as the difference between ATM and OTM option volatilities. I chose not to use implied volatility smirk as a crash risk measure for two reasons: (1) the majority of crash risk literature relies on Chen et al’s (2001) measures, which are direct measures based on stock return data while implied volatility is less direct, and (2) from a mechanistic perspective, my research does not use options so a measure based on such would be inappropriate.

4.4 *Control Variables*

4.4.1 *Volatility of Trading Volume*

In Kyle's (1985) model of imperfect competition, insider trading strategy is affected by the variance of uninformed trading volume. When this variance is smaller, the market maker assumes that imbalanced buy and sell orders are more likely due to informed trades. In order to limit informed trades, the market maker adjusts price accordingly. When this variance increases, the assumption is that the imbalance is due to random variation in uninformed trading and the associated price adjustment is smaller. I control for volume volatility, *SDVOL*, calculated as the standard deviation of monthly trading volume over A-shares outstanding estimated over the fiscal period (Huddart & Ke, 2007). The sample mean of *SDVOL* is 0.2118 and the median is 0.1595.

4.4.2 *Momentum*

Rozeff and Zaman (1988) and Lakonishok and Lee (2001) both document that insiders' trades are related to past stock returns, though the directionality is unclear due to differences in investing strategy. I control for *MOMENTUM*, the six-month compounded buy and hold return ending on the day before the insiders' trade date. A positive relationship between my dependent variables and *MOMENTUM*, where an insider sells (buys) stocks when prices have risen (fallen), may indicate the presence of inside information or simply contrarian strategy. The mean and median of *MOMENTUM* are 0.0984 and 0.0065 respectively. These values correspond to a return rate of 9.84% and 0.65%.

4.4.3 *Stockholdings*

Insiders often cite portfolio diversification and rebalancing as reasons for trading stock. Ofek and Yermack (2000) show that insiders tend to sell stock when they receive new stock

options. Larger trades are likely to be associated with larger insider stock holdings. I calculate *STOCKHOLDINGS* as a percentage of total A-shares outstanding and anticipate that it is positively related to *SALES VP*. Since this variable is calculated on an individual basis, I construct *STOCKHOLDINGSFY* and *STOCKHOLDINGSFHY* when my dependent variable is net sales to control for firm-year and firm-half-year stockholdings.

4.5 Models

I examine each hypothesis with its own set of regressions. My first hypothesis measures the association between prior period crash risk and sales value percentage:

$$SALES VP_{i,y,t} = a_{i,t} + B_1 Crash_{i,y,t-1} + B_2 SDVOL_{i,y,t} + B_3 MOMENTUM_{i,y,t} + B_4 STOCKHOLDINGS_{i,y,t} + \epsilon_{i,y,t} \quad (4)$$

where *SALES VP_{i,y,t}* is the sales value percentage for an insider transaction conducted by an individual *y* for stock *i* at time *t*. *Crash_{i,y,t-1}* is one of my crash risk measures, where *t-1* indicates I calculate prior year crash risk. *SDVOL*, *MOMENTUM*, and *STOCKHOLDINGS* are my control variables. Based on hypothesis 1A, I expect *B₁* to be positive and significant.

Hypothesis 1B separates crash risk into “high” and “low” groups and then performs the same regression as H1. I categorize crash risk as “high” if the value is above the median and “low” if it is below the median. My median crash risk is calculated from my crash risk sample which contains 61,828 observations rather than my smaller insider trading and crash risk sample. Calculating median values from the smaller sample would not accurately reflect a firm’s crash risk since observations are contingent on a trade having occurred.

The second hypothesis examines the relationship between net sales and prior period crash risk:

$$NETSALES_{i,t} = a_{i,t} + B_1Crash_{i,t-1} + B_2SDVOL_{i,t} + B_3MOMENTUM_{i,t} + B_4STOCKHOLDINGS_{i,t} + \epsilon_{i,t} \quad (5)$$

where $NETSALES_{i,t}$ is an aggregate of total trade value for firm i for measurement period t , which is either a fiscal year or a fiscal half-year. My approach with $Crash$ remains unchanged from hypothesis 1A. I adjust $STOCKHOLDINGS$ to a firm-year or firm-half-year level to account for the variable in aggregate. From hypothesis 2, I anticipate B_2 to be positive and significant.

My third hypothesis examines the impact of corporate governance on the insider trading – crash risk relationship. Specifically, I examine whether the observed relationship is weaker within state-owned enterprises compared to non-SOEs. Within my sample, I categorize a company as state-owned when the ultimate shareholder is the state and classify it as a non-SOE when it is not.

$$SALESVP_{i,y,t} = a_{i,t} + B_1Crash_{i,y,t-1} + B_2SDVOL_{i,y,t} + B_3MOMENTUM_{i,y,t} + B_4STOCKHOLDINGS_{i,y,t} + B_5Crash_{i,t-1} * SOE_{i,t} + B_6SOE_{i,t} + \epsilon_{i,y,t} \quad (6)$$

where $Crash * SOE$ is my interaction term measuring the impact of company status on crash risk's effect on insider sales. Based on hypothesis 3, I expect B_5 to be negative and significant, indicating that SOE status attenuates the crash risk – insider trading relationship.

Since a single stock can be traded upon numerous times within a measuring period, some stocks in my sample contribute many data points. I account for this non-independence by using a generalized linear mixed-effects model (GLMM) which allows me to delineate my variables into random and fixed effects. GLMM generates independence by removing stock and year autocorrelation. Since my initial data is temporally autocorrelated, my random effects approach neutralizes individual stock price differences without removing a degree of freedom while my

fixed effects allow me to test my dependent variables. My model computes Satterthwaite's (1946) effective degrees of freedom and applies this to perform Welch's t-test (1947). One advantage of Welch's t-test over the more common Student's t-test is its robustness given unequal sample sizes and variances between groups. I report Nakagawa and Schielzeth's (2013) R^2 values. Marginal R^2 represents variance explained by fixed factors while conditional R^2 represents variance explained by both fixed and random factors.

5. Empirical Analysis

Table 2 displays the summary statistics of the variables of interest in my study. The average percentage value of an insider sale is about 0.0173% of firm value. Based on mean firm value from Table 1, this corresponds to a renminbi value of ¥1,978,766. The mean values for my net sale variables indicate that insiders primarily sought to sell shares in any given firm-year. I measure crash risk using *COUNT*, *NCSKEW*, and *DUVOL* – greater values correspond with a greater degree of crash risk. An average individual insider holds approximately 1.5% of a firm's shares. *MOMENTUM* captures the six-month raw return of a stock prior to an insider trade; my results report an average return of 9.842%. Lastly, *SDVOL* captures the volatility of trading volume over A-shares and I report an average value of 0.2118. This figure is quite large due to the dominance of retail investors in the trading space as greater trading volume from uninformed sources leads to greater trading volume volatility.

Table 2: Summary Statistics of Crash Risk and Insider Trading Variables

My sample period consists of 2223 sales transactions, 588 firm-years, and 722 firm-half-years. *NETSALE* and *NETSALE6* are reported in units of CNY 1000. *SALES VP* is reported as a percentage of total firm value.

	<i>1st Qu.</i>	<i>Median</i>	<i>Mean</i>	<i>3rd Qu.</i>	<i>SD</i>
SALES VP	0.0020	0.0063	0.0173	0.0180	0.03233
NETSALE	-5,379.85	39.422	15,386.749	17,167.351	64,809.020
NETSALE6	-4,474.54	89.938	7,594.878	12,308.590	53,602.383
COUNT _{m,t-1}	0	0	-0.04554	0	0.48578
NCSKEW _{m,t-1}	-0.04657	-0.00453	-0.00032	0.04101	0.06960
DUVOL _{m,t-1}	-0.77454	-0.09321	-0.04580	0.57722	1.04657
STOCKHOLDING	0.00002	0.000373	0.015035	0.00242	0.10972
MOMENTUM	-0.1376	0.0417	0.09842	0.28015	0.35646
SDVOL	0.084848	0.159476	0.211795	0.262959	

Table 3 presents the Pearson correlation matrix for my explanatory, response, and control variables. The results demonstrate strong correlations among crash risk measures ($p < 0.01$), which is similar to prior studies (eg. Chen et al., 2001; Callen & Fang, 2015). For comparison, Callen and Fang's correlation matrix show $NCSKEW * DUVOL = 0.90$, $CRASH * NCSKEW = 0.49$, and $CRASH * DUVOL = 0.69$ while my matrix for the respective combinations are 0.91, 0.59, and 0.52.

The highly significant and positive relationships $SDVOL-STOCKHOLDING$ and $SDVOL-MOMENTUM$ were theoretically expected, as was the lack of significance between $STOCKHOLDING-MOMENTUM$. Among dependent variables, the correlation between $NETSALE$ and $NETSALE6$ is 0.86 ($p < 0.01$) was anticipated, as they capture the same data but within different sized periods. $SALES VP$ is negatively correlated with my net sales variables ($p < 0.05$).

Table 3: Correlation Matrix

Table 3 reports the month-specific crash risk measures used in my first two hypotheses. The superscripts *, **, and *** report statistical significance at the 10%, 5%, and 1% level, respectively.

	<i>COUNT_{m,t-1}</i>	<i>DUVOL_{m,t-1}</i>	<i>NCSKEW_{m,t-1}</i>	<i>MOMENTUM</i>	<i>SDVOL</i>	<i>STOCKHOLDINGS</i>	<i>NETSALE</i>
<i>DUVOL_{m,t-1}</i>	0.52***						
<i>NCSKEW_{m,t-1}</i>	0.59***	0.91***					
<i>MOMENTUM</i>	-0.01	-0.01	0.01				
<i>SDVOL</i>	-0.05***	-0.04**	-0.03*	0.07***			
<i>STOCKHOLDINGS</i>	-0.20***	-0.04**	-0.05**	-0.01	0.12**		
<i>NETSALE</i>	-0.03**	0.03*	0.02	0.10***	-0.09***	-0.03**	
<i>NETSALE6</i>	-0.03**	0.03*	0.01	0.13***	-0.06***	-0.04***	0.86***

5.1 Regression Results

Table 4 presents the regression results of hypotheses 1 and 2, examining the effect of prior year crash risk on the different measures of insider trading activity. Table 4 shows how individual insider trading and aggregated firm-year and firm-half-year insider trading responds to crash risk after controlling for firm-specific characteristics. The estimated coefficients are all significantly positive for my first response variable, *SALES VP*, confirming the positive effect of crash risk on the value of an individual insider's sale. Prior year *DUVOL* has the strongest association with *SALES VP* (t -statistic = 5.216). The corresponding estimated coefficient is 0.00031 and mean sales value is 0.0173%, so an increase in prior year down-to-up volatility by one standard deviation (1.04657) corresponds with a $\frac{0.00031 * 1.04657}{0.0173} = 1.875\%$ increase in mean sales value. *NCSKEW* has a similarly strong association (t -statistic = 4.064) and while its associated coefficient is higher than *DUVOL* (0.00354), the mean and standard deviation of *NCSKEW* are much lower. An increase in *NCSKEW* by one standard deviation (0.0696) yields an increase in average insider sales value of 1.424%. With the weakest association (t -statistic = 2.545), *COUNT* yields an estimated coefficient of 0.00029. An increase in *COUNT* by one standard deviation (0.48578) increases average insider sales value by 0.814. Based on the average sales value (¥1,042.147) found in Table 1, a one standard deviation increase in prior year crash risk may result in individual insiders increasing a single sale transaction by up to ¥19,540. Therefore, the effect of prior crash risk on insider sales value is not only statistically significant, but also economically meaningful.

I note that *SDVOL* is insignificant in my *SALES VP* regressions yet highly significant in *NETSALE* and *NETSALE6*. This result is somewhat surprising as Kyle's (1985) model of imperfect competition explains that insider trading strategy is influenced by net stock volume

variance. One explanation is that my regression is conditioned on an insider's decision to sell, so the only strategic decision is the volume of shares. Testing the relationship on all trades (untabulated) rather than only sale transactions finds *SDVOL* to have a significant impact on trade value as a percentage of total market value ($p < 0.01$). A third test using raw sales value finds *SDVOL* has minimal influence, indicating that *SDVOL* is valuable in determining an insider's decision to buy or sell but less so in terms of the amount they intend to trade. My results from my aggregated trade value regressions are qualitatively similar to Huddart and Ke (2007). Overall, my results demonstrate that *SDVOL* has a significant and negative effect on insider sales. The influence of *MOMENTUM* on the aggregate trade value variables follows my predictions based on prior research (Rozeff & Zaman, 1988). The positive directionality demonstrates the tendency for insiders to sell (buy) when stock prices steadily increase (decrease) over a prior six month period. This contrarian trading behaviour is well documented within insider literature (eg. Seyhun, 1992; Lakonishok & Lee, 2001; Jenter, 2005). Fama and French (1988) find that a portion of insider profits may due to contrarian trading, due to the mean-reverting nature of stock returns. *MOMENTUM*'s larger impact on *NETSALE6* seems to indicate that insiders time their trading decisions, choosing to sell their positions within the initial six months of increasing stock price. Typical insiders are over-exposed to their firms' idiosyncratic risk due to compensation in the form of stock options which cannot be traded or hedged, and the intimate linkage between their human capital value and firm performance (Malmendier & Tate, 2002). This under-diversification requires that risk-averse insiders exercise their options early given a sufficiently high stock price (Lambert, Larcker, & Verrecchia, 1991). Insiders with less risk-aversion are more likely to hold on to their shares or purchase new shares. The effect of *MOMENTUM* on *SALES VP* is significant at 5% and the negative directionality

implies that individual insiders' sales value increases when stock prices have decreased in the preceding six months. Prior studies researching the relationship between momentum and insider behaviour focus on aggregate insider trades and reveal contrarian tendencies. My study reveals how individual insiders choose to offload their shares when the firm has performed poorly, which is an indicator that these insiders do not apply contrarian strategy.

As anticipated, an individual insider's stockholdings has a significant and positive influence ($p < 0.001$) on the volume and value of shares he chooses to sell. Testing this on raw sales value yields qualitatively similar results. Expanding the sample to include both purchase and sale transactions reduces the impact of stockholding, which provides support for Ofek and Yermack's (2000) conclusion that insider sales are driven by a need to rebalance and diversify portfolios. *STOCKHOLDINGS* has a negative and significant relationship with *NETSALE* and *NETSALE6*. This relationship may be influenced by certain factors specific to the aggregate variable - in scenarios where an insider makes a first-time purchase; their *STOCKHOLDING* value is zero, down-weighting the variable. When I examine the effect of aggregate stockholding on a sample where net sales are positive, I find the stockholding variable to be significantly positive with a very large t-value (55.393). This finding confirms that *STOCKHOLDINGS* is a significant influencer in insider sales transactions but not purchase transactions.

Table 4: Regression Results for Hypothesis 1A and 2

NETSALE and *NETSALE6* column values are reported in units of CNY 1000. *STOCKHOLDING* is an aggregated firm-year and firm-half-year value for *NETSALE* and *NETSALE6*, respectively. T-values are included in brackets. I include both year and industry fixed effects. The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: COUNT_{m, t-1}

	<i>SALES VP</i>	<i>NETSALE</i>	<i>NETSALE6</i>
<i>Intercept</i>	0.00127*** (5.621)	10,382.03* (1.83)	4613.48 (1.659)
<i>COUNT_{m, t-1}</i>	0.00029** (2.545)	-10,329.98*** (-5.83)	-6453.79*** (-5.153)
<i>MOMENTUM</i>	-0.00043** (-2.467)	8,371.82*** (2.92)	18,934.05*** (7.348)
<i>SDVOL</i>	0.00056 (1.011)	-35,466.76*** (-5.29)	-26,581.76*** (-4.558)
<i>STOCKHOLDING</i>	0.03059*** (11.063)	-9,033.35*** (-15.01)	-5,842.43*** (-17.482)
<i>N</i>	2230	588	722
<i>Marginal R2</i>	8.567%	10.359%	7.431%
<i>Conditional R2</i>	51.942%	59.463%	51.575%

Panel B: NCSKEW_{m,t-1}

	<i>SALES VP</i>	<i>NETSALE</i>	<i>NETSALE6</i>
<i>Intercept</i>	0.00128*** (5.802)	11,299.10* (1.926)	5,116.27* (1.82)
<i>NCSKEW_{m,t-1}</i>	0.00354*** (4.064)	-113.30 (-0.009)	-7152.26 (-0.84)
<i>MOMENTUM</i>	-0.00049*** (-2.890)	8,230.40*** (2.849)	18,841.06*** (7.306)
<i>SDVOL</i>	0.00052 (0.962)	-36,714.30*** (-5.453)	-27,107.47*** (-4.664)
<i>STOCKHOLDING</i>	0.03030*** (10.982)	-8,483.70*** (-14.2)	-5,558.11*** (-16.825)
<i>N</i>	2230	588	722
<i>Marginal R2</i>	8.653%	9.843%	7.261%
<i>Conditional R2</i>	51.964%	58.988%	51.326%

Panel C: DUVOL_{m,t-1}

	<i>SALES VP</i>	<i>NETSALE</i>	<i>NETSALE6</i>
<i>Intercept</i>	0.00130*** (5.95)	11,346.15* (1.927)	5,219.91* (1.850)
<i>DUVOL_{m,t-1}</i>	0.00031*** (5.216)	300.39 (0.347)	245.98 (0.7669)
<i>MOMENTUM</i>	-0.00050*** (-2.978)	8,164.56*** (2.824)	18,716.07*** (7.244)
<i>SDVOL</i>	0.00053 (-0.979)	-36,746.26*** (-5.46)	-27,212.96*** (-4.689)
<i>STOCKHOLDING</i>	0.02971*** (10.802)	-8,476.50*** (-14.182)	-5,554.03*** (-16.805)
<i>N</i>	2230	588	722
<i>Marginal R2</i>	9.042%	9.844%	7.220%
<i>Conditional R2</i>	51.880%	58.991%	51.323%

Table 5 examines the crash risk – insider trading relationship when I categorize crash risk into high and low subsamples. For all three crash risk measures, I see that the observed relationship is positive and significant when crash risk is high and insignificant when crash risk is low. My reasoning is that high crash risk presents bad news that insiders may believe to be unmanageable, thus representing an untenable degree of risk. The rational response to high crash risk is to offload shares and mitigate firm-specific exposure. In low crash risk scenarios, insiders have greater control over the leakage of bad news and can better time their trades to take advantage of crash risk exposure. Specifically, an insider may anticipate share price to revert to the mean and will hold on to their shares until then.

The results for my second hypothesis regarding aggregated insider transactions are less conclusive. Though *COUNT* has a significant effect on *NETSALE* and *NETSALE6*, the directionality of the crash risk measure is not in line with my hypothesis. An additional test using *CRASH*, a dummy variable that equals 1 if *COUNT* is greater than 0, yields qualitatively similar results. The directionality of the influence of *NCSKEW* and *DUVOL* on aggregate trade value is positive, though their impact is quantitatively insignificant. I believe that these inconclusive results may be due to sample size as my sample only has 588 firm-years and 722 firm-half-years, compared to 4142 individual transactions. Ignoring the possible sample size effects, H2 combines both purchases and sales while H1 focuses solely on sales transactions. As demonstrated in Table 5, the level of crash risk also affects how much stock an insider sells, indicating that individual insiders demonstrate unique levels of risk tolerance. Additionally, individual insiders may also interpret firm crash risk differently due to unequal access to information. This is consistent with the “information hierarchy” as suggested by the evidence in Seyhun (2000), who finds that higher-level executives possess better information about the firm.

Overall, these aspects combine to form significant noise in my findings, which may contribute to my inconclusive results. I also test H2 using aggregate insider transactions on a monthly basis and net sales value as a percentage of firm value but find similarly inconclusive results. This allows me to conclude that crash risk is not a valuable predictor for aggregate insider transactions.

Table 5: Regression Results for Hypothesis 1B: High and Low Crash Risk Groups

Table 5 splits crash risk into high and low groups based on median values from my crash risk sample and examines the association between high (low) crash risk and *SALES VP*. T-values are included in brackets. I include both year and industry fixed effects. The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: COUNT_{m, t-1}

	<i>High Crash Risk</i>	<i>Low Crash Risk</i>
	Sales VP	Sales VP
<i>Intercept</i>	0.01732*** (4.453)	0.01158*** (4.216)
<i>COUNT_{m, t-1}</i>	0.00724*** (2.809)	0.00171 (1.307)
<i>MOMENTUM</i>	-0.00437 (-1.593)	-0.00521** (-2.132)
<i>SDVOL</i>	-0.00274 (-0.270)	0.00845 (1.097)
<i>STOCKHOLDING</i>	0.27011*** (7.36)	0.44810*** (8.654)
<i>Marginal R²</i>	9.0354%	9.2449%
<i>Conditional R²</i>	64.109%	50.4973%
<i>N</i>	995	1194

Panel B: NCSKEW_{m, t-1}

	<i>High Crash Risk</i>	<i>Low Crash Risk</i>
	Sales VP	Sales VP
<i>Intercept</i>	0.01488 ^{***} (4.472)	0.00937 ^{***} (2.840)
<i>NCSKEW_{m, t-1}</i>	0.03219 ^{***} (2.806)	0.00777 (0.554)
<i>MOMENTUM</i>	-0.00615 ^{**} (-2.412)	-0.00495 [*] (-1.88)
<i>SDVOL</i>	0.01268 (1.321)	0.01416 [*] (1.800)
<i>STOCKHOLDING</i>	0.24910 ^{***} (7.484)	0.60950 ^{***} (9.602)
<i>Marginal R²</i>	8.5851%	12.4833%
<i>Conditional R²</i>	58.0339%	56.8593%
<i>N</i>	1032	1157

Panel C: DUVOL_{m, t-1}

	<i>High Crash Risk</i>	<i>Low Crash Risk</i>
	Sales VP	Sales VP
<i>Intercept</i>	0.01538 ^{***} (4.092)	0.01024 ^{***} (4.375)
<i>DUVOL_{m, t-1}</i>	0.00258 ^{***} (3.516)	0.00046 (0.449)
<i>MOMENTUM</i>	-0.00630 ^{**} (2.598)	-0.00387 (-1.636)
<i>SDVOL</i>	0.01354 (1.405)	0.00748 (1.168)
<i>STOCKHOLDING</i>	0.29940 ^{***} (7.689)	0.53970 ^{***} (0.243)
<i>Marginal R²</i>	8.5938%	0.177755
<i>Conditional R²</i>	69.6322%	0.306461
<i>N</i>	937	1252

Table 6 present the results of hypothesis 3, where I examine the impact of SOE status on the crash risk – insider trading relationship. For my first crash risk measure, *COUNT*, SOE status has little impact on the strength of the crash risk – *SALES VP* relation. I attribute this to the categorical nature of *COUNT* such that differences based on SOE status are not adequately captured. In my *NCSKEW* and *DUVOL* measures, the relationship between crash risk and *SALES VP* is significantly weaker for state-owned enterprises than non-SOEs. This confirms my hypothesis on the effects of corporate governance on insider trading behaviour. Specifically, the insiders in SOEs are less involved in business operations (Zhu et al., 2014) which lowers their ability to make informative trades. Additionally, the “quasi-official” status of SOE insiders reduces their motivation to trade profitably – even if they have the knowledge to do so – as they face greater regulatory scrutiny and risk promotion opportunities.

For all regressions, I find variance inflation factors (VIF) to be less than 2, suggesting that multicollinearity does not pose a serious problem in my results (O'Brien, 2007).

Table 6: Regression Results for Hypothesis 3: Moderating Effect of SOE Status

Table 6 features both the individual and interaction effects of SOE status. Hypothesis 3 focuses on the interacting effect of SOE status on the relationship between crash risk and sales value percentage. My sample includes 3915 observations with 1539 SOEs and 2376 non-SOEs. T-values are included in brackets. I include both year and industry fixed effects. The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: COUNT_{m, t-1}

<i>Intercept</i>	0.01707*** (6.355)
<i>COUNT_{m t-1}</i>	0.00302** (2.392)
<i>MOMENTUM</i>	-0.00413** (-2.331)
<i>SDVOL</i>	0.00595 (1.073)
<i>STOCKHOLDING</i>	0.28930*** (10.556)
<i>SOE</i>	-0.00970*** (-3.031)
<i>COUNT_{m t-1}*SOE</i>	-0.00104 (-0.339)
<i>Marginal R²</i>	10.191%
<i>Conditional R²</i>	50.625%
<i>N</i>	3915

Panel B: NCSKEW_{m, t-1}

<i>Intercept</i>	0.01715*** (6.496)
<i>NCSKEW_{m t-1}</i>	0.04414*** (4.376)
<i>MOMENTUM</i>	-0.00478*** (-2.473)
<i>SDVOL</i>	0.00613 (1.114)
<i>STOCKHOLDING</i>	0.28540*** (10.46)
<i>SOE</i>	-0.00994*** (-3.125)
<i>NCSKEW_{m t-1} *SOE</i>	-0.04226** (-2.05)
<i>Marginal R²</i>	10.554%
<i>Conditional R²</i>	50.634%
<i>N</i>	3915

Panel C: DUVOL_{m, t-1}

<i>Intercept</i>	0.01744*** (6.695)
<i>DUVOL_{m, t-1}</i>	0.00381*** (5.66)
<i>MOMENTUM</i>	-0.00500*** (-2.913)
<i>SDVOL</i>	0.00615 (1.125)
<i>STOCKHOLDING</i>	0.27810*** (10.244)
<i>SOE</i>	-0.01021*** (-3.232)
<i>DUVOL_{m, t-1}*SOE</i>	-0.00345** (-2.434)
<i>Marginal R²</i>	10.955%
<i>Conditional R²</i>	50.428%
<i>N</i>	3915

5.2 Robustness Tests

5.2.1 Crash Risk as Public Information

Due to the public nature of prior year crash risk, the relationships explored in H1 and H1B may be driven by market sentiment rather than inside information. Using daily stock return data, I construct a new variable, *market VP*, which replace *SALES VP* in my regression. *Market VP* is calculated as total daily stock trading value divided by total market value and is used as a proxy for a market reaction to crash risk. I compare my result against the coefficient from my first regression (Eq. 4) to determine the relative impact of crash risk on my response variable. I anticipate that the crash risk – insider sales relationship will be stronger as insider sales are more informed by prior crash risk while non-insider trades are less informed in general and less informed by prior crash risk specifically.

$$MARKET VP_{i,t} = a_{i,t} + B_1 priorCrash_{i,t-1} + B_2 SDVOL_{i,t} + B_3 MOMENTUM_{i,t} + B_4 STOCKHOLDINGS_{i,t} + \epsilon_{i,t} \quad (7)$$

where all variables remain the same from hypothesis 1A (Eq. 4) but I change my dependent variable to *MARKET VP*_{*i,t*} which represents the value of daily firm-specific transactions as a percentage of total firm value. This variable is similar to *SDVOL* in that it measures market sentiment but has the advantage of allowing me to compare coefficients across different regressions. Table 7 clearly demonstrates the difference between *Market VP* and *SALES VP*. For all three crash risk measures, insider sales are more strongly affected than market transactions. Therefore, despite the public's access to prior crash risk information, insiders still possess a better ability to process and understand the value of this information when considering their firm-specific stock transactions. This is in line with prior research demonstrating that insiders are better informed than the public (eg. Jaffe, 1974; Finnerty, 1976; Rozeff & Zaman, 1988; Seyhun,

2000). Insiders possess a macro information advantage that provides them with more contextual knowledge in comparison to external investors. This allows them to predict macroeconomic trends and detect deviations in systematic valuation in the market (Zhu et al, 2014). This macro information advantage trickles down to inform firm-specific valuations. It is also important to note that the counterparty to an insider transaction is a retail investor, a group that is not particularly investment savvy.

Table 7: Market Reaction to Crash Risk

I include my original H1 regressions alongside the market value percentage regressions for comparison. The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The effect of crash risk on insider sales is significantly stronger than on market transactions. A similar test conducted only on market sales yields qualitatively similar results.

	<i>Market VP</i>	<i>Sales VP</i>
<i>COUNT_{m,t-1}</i>	0.06421 (0.745)	0.00029** (2.545)
<i>NCSKEW_{m,t-1}</i>	1.16060** (1.887)	0.00354*** (4.064)
<i>DUVOL_{m,t-1}</i>	0.09282*** (2.218)	0.00031*** (5.216)

5.2.2 Endogeneity

A potential concern with my analysis could be that the relationship between prior crash risk and insider trading value is dynamically endogenous, e.g. prior insider behavior dictates prior crash risk, which then effects current insider trading behaviour. To alleviate this concern, I construct an instrumental variable based on average crash risk of all other firms in the same industry (*IV-COUNT*, *IV-NCSKEW*, *IV-DUVOL*) as classified by the CSRC. Average crash risk in an industry peer group is likely to be correlated with the crash risk of an industry-member firm, since both are subject to similar market dynamics. Simultaneously, I have no reason to believe that such industry crash risk would affect the insider trading decisions of an individual

beyond typical market sentiment. Hence, I expect these measures to be uncorrelated with the error term. In stage 1, I take my endogenous crash risk variable as the dependent variable and use my instrumental variable as an explanatory variable. This regression provides predicted values for my endogenous variable. In stage 2, I return to my original regression model (Eq. 4) and replace my crash risk measure with my predicted value and then estimate values for the parameters using ordinary least squares regression. After controlling for possible endogeneity, individual insider sales value continues to be positively correlated with crash risk. For the case of a single endogenous regressor, Staiger and Stock (1994) suggest that instruments are weak if the first-stage F -statistic is less than ten. The F -statistics from my first-stage regressions are 15.387, 30.934, and 116.16 for *COUNT*, *NCSKEW*, and *DUVOL*, respectively. Therefore, I proceed with my instruments into the second-stage regressions. My model computes the Wherry formula for adjusted R^2 (Yin & Fan, 2001). Table 8 reports the results from the two-stage least squares estimation

Table 8: Instrumental Variable Regression

Table 8 lists the results of my first-stage and second-stage regression with t-statistics in parentheses. My results are qualitatively similar to my findings from hypothesis 1A, alleviating endogeneity concerns. I do not include year or industry fixed effects. The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Industry-year mean COUNT_{m,t-1}

	<i>First Stage Regression</i>	<i>Second Stage</i>
Intercept	0.06223 ^{**} (2.813)	0.01886 ^{***} (7.028)
IV-COUNT_{m,t-1}	0.93353 ^{***} (3.923)	0.059267 ^{***} (2.681)
MOMENTUM	-	-0.00674 ^{***} (-3.756)
SDVOL	-	0.02569 ^{***} (6.021)
STOCKHOLDING	-	0.26338 ^{***} (13.021)
Adjusted R²	-	9.689%

Panel B: Industry-year mean NCSKEW_{m,t-1}

	<i>First Stage Regression</i>	<i>Second Stage</i>
Intercept	0.006489*** (3.968)	0.01374*** (10.503)
IV-NCSKEW_{m,t-1}	0.804636*** (5.563)	0.18110** (2.009)
MOMENTUM	-	-0.00780*** (-4.469)
SDVOL	-	0.02460*** (5.807)
STOCKHOLDING	-	0.26465*** (13.076)
Adjusted R²	-	9.559%

Panel C: Industry-year mean DUVOL_{m,t-1}

	<i>First Stage Regression</i>	<i>Second Stage</i>
Intercept	0.08623*** (4.254)	0.01335*** (11.446)
IV-DUVOL_{m,t-1}	1.02353*** (10.778)	0.00998** (2.527)
MOMENTUM	-	-0.00766*** (-4.390)
SDVOL	-	0.02543*** (5.970)
STOCKHOLDING	-	0.26430*** (13.067)
Adjusted R²	-	9.656%

6. Conclusion and Limitations

The goal of this study was to investigate the empirical association between prior crash risk and insider transactions. As the main core of the article, I test hypotheses focused on individual or aggregate insider transactions. Additionally, I examined how corporate ownership impacts the strength of the crash risk – insider trade value relationship. By employing a prior crash risk measure, I circumvent the causality concerns surrounding crash risk and insider trading, allowing me to effectively examine how insiders trade based on crash risk. The prior crash risk measure has the additional benefit of being wholly public information, allowing me to compare how insiders and external traders react to the same information. The results indicate that insiders react more strongly to crash risk than external traders, which indicates that insiders still possess some form of information advantage. I conclude that this information advantage exists in two ways. Firstly, insiders have a greater capacity to assess the underlying and long-term effects of prior crash risk on current stockholdings. Future research can examine analyst transactions rather than market transactions, as analysts should be better informed about publicly available information yet precluded from private information. Secondly, I believe that existing crash risk measures as defined by Chen et al. (2001) may not fully capture a firm's crash risk and that non-systemic, non-public information also sways an insider's decision to trade against market sentiment.

Both crash risk and insider trading can severely damage investors' welfare and confidence. The consequence of crash risk on insider trading behaviour is especially important, as both the market and shareholders take their cue from disclosed insider trades. Due to the correlated nature of prior, current, and future crash risk, significant insider sales following prior crash risk may signal that prior observed crash risk has not been mitigated. This may result in a

continuing fall in share price as investors lose more confidence in the firm. The Enron scandal is a spectacular example of falling investor confidence after significant stock price crash risk.

Therefore, my analysis here focuses on both science and policy. Science considers the implications of my findings for market efficiency. Policy seeks to determine the effectiveness of current regulations and the implications of insider advantages for market fairness and performance. Prior literature has discussed the benefits of insider trading with regards to improving market efficiency and weighs it against its negative effects on market fairness. In an unregulated market, insiders would profitably trade on private information and the market would ultimately adjust such that firm-specific news would not impact stock price. In a draconian regulatory system, insiders are fully prevented from trading profitably, which increases external investor confidence at the cost of being prohibitively expensive. Unlike the U.S., China's insider trading regulatory system is not sufficiently effective in reducing insider advantage, but the controls put in place in Chinese SOEs demonstrate that insider behaviour following crash risk can be contained. From a fairness perspective, such controls are desirable as they limit insiders from selling stocks on potentially private information. In the event that no private information exists, limiting insider sales is still desirable as it alleviates future stock price crash risk. Firms can implement measures that protect shareholder welfare in addition to firm health. An ex-ante preventative measure such as a policy requiring approval by the firm's general counsel prior to an insider sale would serve to limit exploitative trading (Dai et al., 2016). In addition to ex-ante preventative measures, well-governed firms may use ex-post disciplinary measures such as fines or forced turnovers to discourage other insiders from engaging in undesirable trading.

Future research needs to account for abnormal returns after insider trades to determine if trades motivated by crash risk lead to greater trading profits. Additionally, these studies can also

examine if managers can time their trades effectively to maximize profits and minimize legal jeopardy. From a mechanistic perspective, this study could be better improved with the use of rolling crash risk measures rather than the month-specific measures I employed. This would allow for a unique crash risk measure for each insider transaction. Future studies would also benefit from a larger sample in terms of both number of firms studied and period of study. My study focuses only on A-shares in the Shanghai Stock Exchange but future studies can expand to other Chinese stock exchanges including the Shenzhen Stock Exchange (SZSE) and Hong Kong Stock Exchange (HKEX). China currently uses A, B, and H shares which trade under different denominations and bylaws, so special consideration is required when studying these different share types. A larger sample also benefits the study of aggregate insider transactions – my *NETSALE* and *NETSALE6* regressions both utilized limited samples and found inconclusive results. There is also justification for using a one-month aggregation period, which has the benefit of increasing observations and limiting noise associated with larger aggregation periods, but suffers from overrepresentation from large individual transactions driven by non-crash risk related information. Future research should strive to control for information hierarchy by categorizing insider trades based on insider status within the firm - Seyhun (2000) defines a “director month” as one where directors trade the greatest dollar amount of stock during that month. Finally, while I control for firm size in my variable construction, it would be interesting to segregate firms into size quintiles and observe how firm size influences the crash risk - insider trading relationship.

To conclude, this paper seeks to analyze whether prior crash risk affects insider trading. Using a Chinese dataset of disclosed insider transactions, I examine whether insiders can effectively use publicly available prior crash risk information to inform their trades. In particular,

I seek to contribute to the literature in four ways. First, I demonstrate how to use crash risk as a predictor variable by using prior crash risk in my regressions, allowing me to draw meaningful conclusions about its impact on insider sales. Secondly, I examine how insiders can form an information advantage using only public information through their enhanced capacity to assess such information. Alternatively, my study demonstrates that crash risk measurements may not adequately capture a firm's crash risk, indicating that future research can expand on Chen et al. (2001) calculations. Thirdly, I contribute to the extant literature documenting the moderating effect of corporate governance on insider trading with a unique use of SOE status as an indicator. Finally, my study complements previous studies by observing an emerging market. China possesses a number of unique characteristics that make it a ripe study for insider trading, namely its weak and politically motivated legal system, highly concentrated corporate ownership, recent transition to free market share trading, and high percentage of retail investors. My results suggest the following conclusions.

First, looking across all firms and insider transactions, my estimated results are supportive of a positive relationship between prior crash risk and insider sales value. This is consistent with my intuitive belief that insiders opt to sell shares in the presence of crash risk. I further tested this hypothesis by subsampling crash risk into high and low groups to examine the potential for insiders to buy shares in the presence of crash risk – I determined that high crash risk is correlated with high selling activity while low crash risk yields insignificant transactional activity. It is important to note that my estimated results for aggregate insider transactions were inconclusive and that this requires further research in the future.

Second, I established that there are significant differences between SOEs and non-SOEs in terms of insider motivations and restrictions. Significantly, insiders within state-owned

enterprises chose to limit their share sales in the presence of crash risk. However, my research does not allow us to determine if this sale limitation is due to a lack of business understanding or an unwillingness to engage in trading that may be interpreted as information-driven. In sum, my results support the view that individual insider sales are driven by prior crash risk and that external investors are not effectively utilizing this source of public information.

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