The Impacts of Dark Trading and Block Trading on Firm Valuation and Default Risk

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The thesis is submitted to La Trobe University in total fulfilment of the requirements for the degree of Doctor of Philosophy

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Victoria, Australia

April 2020

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Acknowledgements

First and foremost, I would like to express my deepest gratitude to my supervisors, Associate Professor Jing Zhao and Associate Professor Daisy (Hsin-I) Chou for their valuable guidance, warm encouragement, and continuous support throughout my PhD candidature at La Trobe University. From the beginning of my research journey until the very last stage of my PhD thesis, they convincingly guided and encouraged me to be professional and do the right thing even when the road got tough. I particularly thank Associate Professor Jing Zhao. Without the dedicated supervision and patience from her, this thesis would not have been realized.

I wish to thank all the staff in the Department of Economics and Finance at La Trobe University whose assistance was a milestone in the completion of this project. I am especially thankful to Associate Professor Darren Henry, Dr Weifang (Angela) Lou, Dr Tu Nguyen, and Dr Weihan Liu for their encouragement and invaluable advice.

I truly appreciate the support and great love given by my family - my wife, Bing Huang; my mother, XiaoLi Jiang; and my father, PeiXin Liu. I also thank my parents-in-law, MeiLing Wang and JianJun Huang, for their understanding, support and encouragement. They encouraged me to keep going and this work would not have been possible without their input. Last but not the least, I would also like to thank my son Dylan Xundi Liu and daughter Arianna Qinyi Liu for accompanying me on this challenging PhD journey.

Abstract

The emergence of dark pools has made it possible to trade with less pre-trade transparency. This thesis examines the impacts of dark trading and block trading on firm valuation and default risk using a sample of Australian stocks during the 2005-2015 period. We find that firms with more dark trading tend to have less market valuation. Block trading activities are executed through upstairs brokers with limited pre-trade transparency. We find an insignificant effect of block trading on firm value. Our results are robust to various endogeneity tests. To establish the causal effect of dark trading, we use an instrumental variable approach and a difference-in-differences approach that relies on exogenous shocks to dark trading. We examine three mechanisms through which dark trading could harm firm valuation: decreasing stock liquidity; reducing stock price informational efficiency; and impeding corporate governance by blockholders. We show that dark trading can damage stock liquidity, and its effect on firm value is stronger for stocks with lower liquidity. Firms with more dark trading are found to have higher default risk, although block trading has no effect. Apart from the three mechanisms examined on the topic of firm value, we explore financial constraints as a possible mechanism for dark trading as influencing default risk. Of the four mechanisms we find that the stock liquidity channel has the highest explanatory power. We also demonstrate that the effect of dark trading on firm default risk is not mechanical via decreased firm value, and residual effects of dark trading on firm value and default risk do exist, even after controlling for the underlying mechanisms. Taken together, this thesis reveals two adverse real effects of dark trading in terms of reducing firm value and increasing firm default risk.

Statement of Authorship

I, YuanPeng Liu, declare that:

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YuanPeng Liu,

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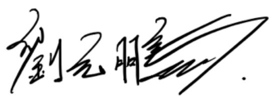

Chapter 1

Introduction

1.1 Research Background

Dark trades are the trades executed without pre-trade transparency. In other words, traders are not requested to reveal order details to the public until the orders have been filled. Dark pools are the equity trading systems that systematically match orders without pre-trade transparency and enable them to be executed away from exchange markets. All the orders are placed anonymously in dark pools. Compared with traditional exchange markets (known as lit markets) in which buy and sell orders are visible and accessible before execution (known as lit orders), dark orders are not visible until they are filled in within dark pools resulting in dark trades.

The Australian Securities and Investments Commission (ASIC) defines dark pools as electronically accessible pools of liquidity that are not pre-trade transparent, including crossing systems and dark venues operated by exchange market operators (ASIC, 2013).[1] As alternatives to lit markets, dark pools have emerged and grown rapidly in recent years. As of March 2015, there were 17 crossing systems operated by 15 market participants, in addition to the two dark venues operated by stock exchanges (ASIC, 2015).[2] Before the emergence of dark pools, market participants have long used block orders to prevent order details from being revealed to the market prior to the order execution. Block orders are managed by upstairs brokers and placed for the sale or purchase of a large number of securities. In recent years, a substantial amount of trading activities is executed without pre-trade transparency around the

[1] Available at: https://download.asic.gov.au/media/1344182/rep331-published-18-March-2013.pdf.

[2] Available at: https://download.asic.gov.au/media/3444836/rep452-published-26-october-2015.pdf.

world, in the form of dark trades and block trades (Comerton-Forde and Putninš, 2015).[3] In addition, financial markets have been transformed by technology and High-Frequency Trading (HFT). Market participants increasingly use algorithms to break large (block) orders into small (dark) orders for execution, making dark executions become even more significant (Banks, 2010).

The substantial growth in dark trading has raised regulatory concerns on whether it harms market efficiency,[4] and prior literature largely focuses on examining the impact of dark trading from the perspective of market microstructure (e.g., Comerton-Forde and Putninš, 2015; Degryse, de Jong, and van Kervel, 2015). However, little is known about the financial implications of dark trading activities for participating firms.

The advantages and disadvantages of dark trading are distinct. On the one hand, dark trading hides pre-trade information before execution. The lack of pre-execution transparency allows investors to minimize information leakage and market impact cost (e.g., Rhodri and Sviatoslav, 2014). As well, dark pools provide lower commission fees to the participants comparing with exchange markets (Conrad, Johnson, and Wahal, 2003; Ray, 2010). However, on the other hand, traders in dark pools are facing high levels of non-execution risk (Keim and

[3] If we consider trading without pre-trade transparency as dark trading, there are two types of dark trading: block dark trading and non-block dark trading. Block dark trading has a minimum trading size requirement while non-block dark trading has no such requirement. Following studies such as Comerton-Forde and Putninš (2015), we call non-block dark trading as dark trading and block dark trading as block trading for the remainder of this thesis.

[4] For instance, the International Organization of Securities Commissions (IOSCO) concerns that "*the development of dark pools and use of dark orders could inhibit price discovery if orders that otherwise might have been publicly displayed become dark*"; see "Principles for Dark Liquidity", Final Report 2011, Technical Committee of the IOSCO.

Madhavan, 1998; Gresse, 2006). Given that dark trading provides both incentives and uncertainty to the traders and is likely to affect corporate information environment, it is interesting to understand whether dark trading activities could change the performance or risk level of the participating firms.

This thesis aims to investigate the financial implications of dark trading activities in the context of the Australian equity market with specific reference to two dimensions. Firstly, it examines the valuation effects on a firm associated with dark trading activities in its stock. It tests whether dark trading increases or decreases firm value and examines the impact of block trading as well. Secondly, it examines the impact of dark trading and block trading on firm default risk, respectively. In both studies, we employ exogenous shocks for dark trading activities to identify the causal effects and investigate the potential mechanisms for the effects.

Our sample comprises the constituents of the All Ordinaries index, which includes the 500 largest stocks listed on Australian Stock Exchange (ASX), covering the period 2005-2015. There are several benefits of investigating the Australian stock market instead of other markets. The ASX operates a transparent central limit order book (CLOB) which matches orders on price-then-time priority. During our sample period, the ASX allows block trades and dark trades, to be executed away from the CLOB, but all trades are required to be reported to the exchange immediately. As a result, the ASX operates a single consolidated source for trading records covering all trade types including lit, dark, and block trades.[5] It enables us to

[5] Loshin (2009, chapter 10) discusses "data consolidation" in the book: "*…because data instances from different sources are brought together, the integration tools use the parsing, standardization, harmonization, and matching*

differentiate various types of trades and have consistent transaction time-stamps across different trading venues.[6] For other markets such as the U.S. market, time-stamps are likely to be inconsistent across trading venues, trade types are not available to the public and the classification of dark and lit trades can be inaccurate (Comerton-Forde and Putninš, 2015), which are common issues in understanding the role of dark trading activities. In contrast, our sample of Australian data allows us to precisely identify and measure dark and block trading activities at an individual stock level.[7] Furthermore, market structure changes in Australia do exist during our sample period and they are exogenous with respect to firm value and default risk; nonetheless they influence dark trading activities. Empirical corporate finance often has serious issues with endogeneity, because it is generally difficult to find exogenous factors or natural experiments with which to establish the causal relationships. The availability of exogenous events in the Australian market enables us to address the potential endogeneity of dark trading. In addition, the Australian data distinguishes the traditional upstairs block trades and smaller dark trades executed without negotiation, although they are both without pre-trade transparency. It helps us to examine their different impacts and understand the implications of the rise of dark pools.

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capabilities of the data quality technologies to consolidate data into unique records…". In Australia, central limit order book (CLOB) is the sole resource with consolidated trading records.

[6] The time-stamp is the time (or say a value as it is a monotonically increasing number) assigned in the order in which the transaction is submitted to the trading system.

[7] All the trades are recorded with "flags" to classify trading types in Australia. The "flags" on limited order book provide accurate classifications to all the trades. Dark trades have flags marked as "Centre Point trades", "Centre Point Crossings", and "Priority Crossings". Block trades have flags marked as "Special Crossings".

This thesis includes two empirical studies examining the effects of dark and block trading activities on firm valuation and default risk, respectively. In what follows, we introduce their motivations, main findings and contributions in separate sections.

1.2 Dark Trading Impacts on Firm Valuation

The first empirical study of this thesis investigates the effects of dark and block trading on firm valuation. It is motivated by the growing literature that links various trading activities in financial markets to firm valuation, including insider trading (Masson and Madhavan, 1991), option trading activities (Roll, Schwartz, and Subrahmanyam, 2009), individual investor trading (Wang and Zhang, 2015b), and trading activities of Credit Default Swaps (CDSs) (Narayanan and Uzmanoglu, 2018). Despite the rapid growth of dark trading in recent decade and the long history of block trading, prior studies are largely concerned about their impacts on market quality from the perspective of market microstructure, yet little is known about their valuation effects. This study is the first one to investigate the impacts of dark and block trading on firm valuation.

Dark trading can decrease firm value for several reasons. Prior literature documents several detrimental effects of dark trading on market quality such as increasing trading costs, impairing stock liquidity, and raising adverse selection risk (see, e.g., Blume, 2007; Foley, Malinova, and Park, 2013; Comerton-Forde and Putninš, 2015). Hatheway, Kwan, and Zheng (2017) argue that the flight of liquidity from lit markets to dark pools reduces price discovery and increases transaction costs for all markets. Weaver (2014) shows dark trading associated with wider spreads, higher price impacts and higher volatilities. In the literature, theoretical arguments and empirical evidence support a relationship between market quality and firm performance. For example, stock liquidity is one of the most important factors of market quality. If stock liquidity is priced by the market, lower liquidity would lead to higher expected return, lower current stock price and less market valuation for the firm (Amihud and Mendelson, 1986). Fang, Noe, and Tice (2009) show that firms with more liquid stocks have better performance. Therefore, reduced stock liquidity induced by dark trading activities could be translated into a firm's lower market valuation. We consider stock liquidity as a possible underlying mechanism for dark trading to reduce firm valuation. Recent theorical work by Zhu (2014) predicts that dark trading leads to partial segmentation of informed trading and uninformed traders, and a higher concentration of informed trading in the lit markets could harm a firm's information environment.

Information asymmetry is costly to a firm as it impedes the firm from raising cheap external capital and forces it to make suboptimal investment decisions (Fauver and Naranjo, 2010; Fosu, Danso, Ahmad, and Coffie, 2016). We thus consider reduced information efficiency as a second possible mechanism for increased dark trading to reduce firm valuation.[8] Added to this, recent studies on the subject of corporate governance advance trading as a method of governance (see, e.g., Admati and Pfleiderer, 2009; Edmans, 2009; Edmans and Manso, 2011), and subsequently reduced market quality caused by increased dark trading could

[8] Roll, Schwartz, and Subrahmanyam (2009) show the relationship between option trading and firm valuation is stronger for stocks with greater information asymmetry. Narayanan and Uzmanoglu (2018) find that the magnitude of CDS trading reducing firm valuation depends on the level of incremental information that trading in CDSs produces.

hinder blockholders from exerting the governance role. It presents a third possible mechanism for dark trading to reduce firm valuation.

While our specific focus is to tests the hypothesis of the negative impact of dark trading on firm valuation, it is worth noting the possibilities for dark trading to increase firm valuation. Prior literature documents evidence on the beneficial impacts of dark trading on market quality. For instance, O'Hara and Ye (2011) argue that the emergence of dark pools leads to more fragmented markets. They find increased market fragmentation reduces transaction costs, improves stock price informational efficiency, and increases execution speed for NYSE and NASDAQ stocks. Using Canadian data and Australian data, Foley and Putninš (2016) show that dark limit order markets can benefit market quality, improve stock liquidity and informational efficiency. The enhanced market quality caused by dark trading could be translated to higher valuation of the firm. Ye and Zhu (2019) develop a theoretical model to show that large informed traders prefer to use dark pools for acquiring a large ownership for intervening in corporate governance, and therefore dark trading could facilitate corporate governance. In addition, motivated by the theoretical arguments of Porter (1992) and Bhide (1993), Fang, Tian, and Tice (2014) find that increased stock liquidity leads to less firm innovation output and it is likely for stock liquidity to impede firm performance. Taken together, whether dark trading reduces or increases firm valuation is ultimately an empirical question, and our study may be viewed as an effort to explain the competing hypotheses.

Block trading is an old form of dark trading that has limited pre-trade transparency and a minimum size requirement of transaction. Although block trading has long been a topic of interest for academic researchers, market practitioners, and regulators (see, e.g., Kraus and

Stoll, 1972; Seppi, 1990; Saar, 2001), how it affects firm valuation is unexplored in the literature. Managed by upstairs brokers, block trading facilitates trades that are difficult to be executed in the CLOB and expands the total available liquidity. Block trades are less likely to be informed compared to lit trades and have the lowest market impact costs compared to other trade types (Ready, 2014; Hatheway, Kwan, and Zheng, 2017). Comerton-Forde and Putninš (2015) find no evidence of block trading impeding price discovery. Given the little impact of block trading on market quality and firms' information environment, we expect no relationship to appear between block trading and firm valuation.

Using a sample of Australian stocks during the 2005-2015 period, we find that firms with more dark trading tend to have less market valuation, as measured by Tobin's Q, which supports a negative impact of dark trading on firm performance. Our results remain robust after controlling for industry and year fixed effects. The effect of dark trading is economically meaningful. In particular, a one-standard-deviation increase in the dark trading variable leads to firm value reduced by over 14% of its mean. As expected, we find little relationship between block trading and firm valuation. It supports prior literature on the minor impact of block trading on market quality and corporate information environment.

We perform several tests to address the endogeneity concerns caused by unobservable omitted variables and the concern of reverse causality. Following Fang, Noe, and Tice (2009), we argue that firm fixed effects can be used as an endogeneity control if the unobservable correlated with dark/block trading and industry-adjusted firm performance remains constant over time. When industry-adjusted counterparts are considered for all variables except for dummy variables and firm fixed effects are controlled for, we still document a negative effect of dark trading on firm valuation and little effect of block trading. In the two-stage least squares (2SLS) regressions, we construct a set of two instruments based on market structure changes following Comerton-Forde and Putninš (2015) to establish a causal effect of dark trading on firm valuation. The removal of the ten-second rule on 30 November 2009 is considered as the first market structure. The ten-second rule requires an ASX broker to place an order in the CLOB for ten-seconds before executing dark trades, and its removal makes the execution of dark trades more convenient. The second market structure change refers to the ASX launching its first exchange-based dark pool called Centre Point in June 2010, and the change in ASX trading fees on 1 July 2010. Both market structure changes are expected to increase dark trading activities but are unlikely to be related to Australian firms' performance.[9]

In the first-stage regressions, we find dark trading dramatically increases (by 97.97% of its mean) after the ten-second rule is removed. The impact of the second market structure change on dark trading is highly significant in statistical terms, but its economic significance is much smaller compared to the removal of the ten-second rule. It confirms both market structure changes as valid instruments and demonstrates the removal of this rule as a better candidate for a quasi-natural experiment of dark trading activities. In the second-stage regressions, we show that the fitted value of dark trading has a significant and negative effect on firm valuation and the effect of the fitted value of block trading is insignificant, and our

[9] Our instrumental variable estimation relies on the assumption that the market structure changes do not directly affect our outcomes of interest (i.e., firm valuation) except through their impact on dark trading activities. This assumption is reasonable in out settings since the considered market structure changes directly affect the convenience of dark trading. However, they are not expected to influence firm performance directly.

findings in the baseline specifications remain robust. To further address the concern of reverse causality, we examine the changes in firm valuation around the removal of the ten-second rule as an exogenous event, and there exists a significant reduction in firm valuation following the year of removal. In addition, we adopt a difference-in-differences approach to establish a causal effect of dark trading on firm valuation and consider the removal of the ten-second rule as an exogenous event. We consider firms with significant changes in dark trading due to the removal of the ten-second rule as the treatment group, and match them with a group of firms that are least affected by the removal event based on propensity score matching so that the treatment and control groups have similar firm characteristics. We show that the exogenous increase in dark trading due to the removal of the ten-second rule leads to a larger relative reduction in firm valuation for the treatment group compared to the control group. The detrimental effect of dark trading on firm valuation is also confirmed in the difference-in-differences regressions.

After establishing the sign of and causality for the relationship of dark trading and firm value, we further explore the potential underlying mechanisms. As discussed above, dark trading could harm firm valuation through its impacts on stock liquidity, stock price informational efficiency, and blockholder ownership. We find that the negative effect of dark trading on firm valuation is stronger for stocks with lower liquidity, although the relationship of dark trading and firm valuation does not vary with information efficiency or blockholder ownership. Our results are robust to alternative measures of stock liquidity. It identifies stock liquidity as a channel for dark trading to harm firm valuation. The effect of block trading on firm valuation remains insignificant and does not vary with variables related to stock liquidity, information efficiency, or blockholder ownership. It confirms there is little impact of block trading on firm valuation.

For additional evidence, we adopt a difference-in-differences approach to test the changes in stock liquidity, information efficiency, and blockholder ownership in the matched sample and relies on the removal of the ten-second rule as an exogenous event which is demonstrated to substantially increase dark trading. We find stock liquidity significantly declines following the exogenous event, while blockholder ownership significantly increases. There is little impact of the exogenous event on stock price information efficiency. Taken together, we demonstrate that dark trading harms firm valuation through reducing stock liquidity. Although blockholder ownership is affected by dark trading, it does not translate into changes in firm valuation. Our results support the findings of Fang, Noe, and Tice (2009) who find that stock liquidity is an important determinant of firm performance. Prior studies document reduced stock liquidity as an undesired consequence of increased dark trading activities (see, e.g., Blume, 2007; Nimalendran and Ray, 2014; Degreyse, de Jong, and Kervel, 2015; Comerton-Forde and Putninš, 2015). Compared to lit trading, dark trading has higher non-execution risk, increases searching costs (Yin, 2005) and reduces the firm's stock liquidity.[10] We reveal a real valuation effect of increased dark trading in terms of poorer firm performance.

To determine whether the causal effect of dark trading on firm valuation identified in this

[10] Handa and Schwartz (1996) conclude that limit order traders are exposed to the non-execution risk which corresponds to a long waiting time on the book. Rouetbi and Mamoghli (2014) argue that the liquidity temporal dimension refers to the speed at which transactions could be concluded. Consequently, investors are exposed to non-execution risk when they are doing dark trades and the high-level non-execution risk introduces illiquidity because of long matching time.

study goes beyond the underlying mechanisms and the existing literature, for instance Fang, Noe, and Tice (2009) document a positive effect of stock liquidity on firm valuation, we disentangle the direct versus the indirect effect of stock liquidity on firm valuation following He and Tian (2013). We find that the underlying mechanism of stock liquidity and blockholder ownership can explain up to 22.8% of the total effect of dark trading on firm valuation, and there is evidence of a significant residual or direct effect for dark trading to influence firm valuation. It suggests a novel role of dark trading in harming firm performance.

To the best of our knowledge, this study is the first to investigate the effects of dark trading and block trading on firm valuation. It contributes to the growing literature on the impacts of dark trading. Given the rapid growth of dark pools and dark trading, the published literature is debating whether dark trades harm or improve market quality from the perspective of market microstructure (see, e.g., Ye, 2010; Zhu, 2014; Kwan, Masulis, and McInish, 2015; Foley and Putninš, 2016) and the results are mixed. In this study, we take a different perspective from corporate finance and directly examine the valuation effect of dark trading. By directly focusing on firm valuation, we not only allow the benefits and costs of dark trading on market quality to offset with each other but also test whether any changes in market quality induced by dark trading can be translated to changes in firm valuation. We show that dark trading harms firm valuation and reveal a detrimental effect of dark trading on the real economy. In addition, we identify the channel of reduced stock liquidity as an underlying channel for increased dark trading to harm firm valuation. It is consistent with stock liquidity as an important factor of market quality.

This study also contributes to the literature of block trading. Prior studies argue that block trading trends to be uninformed (see, e.g., Grossman, 1992; Bessembinder and Venkataraman, 2004; Nimalendran and Ray, 2014), but how block trading affects firm valuation remains unclear. Our study fills the gap in this knowledge and shows there is little relationship between block trading and firm valuation. It complements the existing literature to support little impact of dark trading on market quality, although our focus is on the valuation implications of block trading. Finally, this study is related to the emerging literature that links trading activities to firm valuation. Prior literature on firm performance largely focuses on the impacts of corporate strategies, ownership structure, and governance characteristics (see, e.g., Chaney and Lewis, 1995; Maury and Pajuste, 2005; Ammann, Oesch, and Schmid, 2011; Kraft, Schwartz, and Weiss, 2018).

Recent literature shows that firm performance is positively affected by option trading activities (Roll, Schwartz, and Subrahmanyam, 2009) and individual investor trading (Wang and Zhang, 2015b), and negatively influenced by trading in CDSs (Narayanan and Uzmanoglu, 2018). Our study documents a detrimental effect of dark trading activities and little effect of block trading activities on firm valuation. Our adoption of Australian data enables us to have a consolidated trading record covering all trade types of lit, darks and block trades, and have market structure changes for a quasi-natural experiment to address the endogeneity concerns. This study's findings also have important policy implications because dark trading activities can be eased or hindered through changing financial market regulations. We reveal a real effect of dark trading on reducing firm valuation, raising concerns on the rapid growth of dark pools and dark trading activities.

1.3 Dark Trading Impacts on Default Risk

Default is a failure to meet debt obligations and represents one of the most disruptive events in the life of a corporation. Probability of default captures firm-level financial instability. Financial stability is paramount for economic growth and excessive instability could lead to stock market crashes and even financial crisis. Given the importance of firm default risk for a large number of stakeholders, including firm managers, employees, investors, and regulators, and for the real economy, understanding the factors that increase or decrease firm default risk is a long-standing topic in the literature. However, little is known about how investor trading activities could influence firm default risk, except for Chen, Saffar, Shan, and Wang (2018) and Cao, Hertzel, Xu, and Zhao (2020), who link corporate debt structure to trading in CDSs and trading in options. Given the excessive growth in dark trading and the regulatory concerns about its influence, the second empirical study of this thesis examines the effect of dark trading and block trading on firm default risk.

Dark trading may increase firm default risk for several reasons. First, Boni, Brown, and Leach (2013) show the possibility of institutional investors being exploited by counterparties in dark pools and such predatory behaviors may have significant social costs. Liquidity is often used as a proxy for market quality and there is evidence of dark trading reducing stock liquidity (see, e.g., Weaver, 2014; Comerton-Forde and Putninš, 2015; Degryse, de Jong and Kervel, 2015). Brogaard, Li, and Xia (2017) find a negative causal effect of stock liquidity on firm default risk, and therefore the reduced stock liquidity caused by dark trading could be translated to higher firm default risk. Second, idiosyncratic risk is often considered as an indicator of asymmetric information. Furfine and Rosen (2011) find idiosyncratic risk strongly increases acquirer default risk. They argue it consistent with asymmetric information allowing managers to better hide risk-increasing actions from outside shareholders by interpreting these actions as reflecting a random outcome of greater ex ante uncertainty (Dierkens, 1991). Merton's (1974) structural credit risk model also shows that firm default risk increases with equity volatility. The growth of dark trading leads to more market fragmentation, while Madhavan (1995) indicates that market fragmentation leads to higher volatility and less efficient prices.

In the theoretical model of Ye (2010), dark venues enable informed traders to make large profits in the dark by scaling back the trading aggressiveness in the lit. It suggests that informed traders execute a considerable share of their trades in the dark and more share of dark trading indicates higher level of information asymmetry. Taken together, dark trading could increase firm default risk by making firms' information environment less efficient. Third, Ye and Zhu (2019) find that dark pools facilitate activist traders to obtain large ownership and therefore blockholder ownership is likely to increase with dark trading. Ashbaugh-Skaifea, Collins, and LaFond (2006) show there is a negative relationship between blockholder ownership and firms' credit rating. It suggests dark trading has a positive relationship with firm default risk. Fourth, financial constraints refer to the extent whereby firms are constrained in their ability to raise fund externally. Myers' (1984) pecking order theory argues that firms with more information asymmetry face higher equity costs, and they tend to make suboptimal investment leading to increased default risk (Ryen, Vasconcellos, and Kish, 1997; Fosu, Danso, Ahmad, and Coffie, 2016). Given that dark trading is likely to increase information asymmetry, it could increase firm default risk by making firms more financially constrained.

On the other hand, dark trading may reduce firm default risk. There exists evidence of dark trading improving stock liquidity and information efficiency (see, e.g., Gresse, 2006; Buti, Rindi, and Werner, 2011; O'Hara and Ye, 2011; Foley and Putninš, 2016) and such benefits could be translated to reduced firm default risk (Brogaard, Li, and Xia, 2017). In addition, even if dark trading reduces stock liquidity, the reduced liquidity can alternatively reduce firm default risk if it hinders noise trading, leading to less firm mispricing and lower volatility (see, e.g., Baker, Stein, and Wurgler, 2003; Goldstein and Guembel, 2008; Polk and Sapienza, 2008). Given the mixed evidence on the relationship between stock liquidity and dark trading or firm default risk, it remains an empirical question whether dark trading increases or decreases firm default risk.

Using a sample of Australian stocks during the 2005-2015 period, the second empirical study of this thesis examines the effect of dark trading and block trading on firm default risk. To capture default risk, we calculate the expected default frequency (EDF) based on the approach of Bharath and Shumway (2008) and consider the EDF over a one-year and five-year horizon, respectively.[11] We document a positive effect of dark trading on firm default risk, and the results are robust to alternative measures of default risk estimated over different horizons and remain after controlling for industry and year fixed effects. It shows an undesired consequence of dark trading in terms of increasing firm default risk. A one-standard-deviation increase in the dark trading variable leads to the one-year EDF increased by over 17% of its

[11] Bharath and Shumway (2008) provide a simplified version of Merton's (1974) structural distance-to-default model. They show that their simplified measure of default risk performs slightly better in hazard models and in out-of-sample forecasts than both the Merton model and a reduced-form model. It even subsumes the effect of the Merton distance-to-default measure in predicting CDS spread and bond yield spread.

mean and the five-year EDF increased by over 11% of its mean, which suggests an economically significant impact of dark trading on default risk. There exists little relationship between block trading and firm default risk, which is consistent with the little impact of block trading on market quality and corporate information environment.

To establish the causality and address the endogeneity problem, we adopt an instrumental variable approach and a difference-in-differences approach that rely on exogenous shocks to dark trading. In the instrumental variable approach, we construct a set of two instruments based on market structure changes including: (i) the removal of the ten-second rule on 30 November, and (ii) the launch of Centre Point, the first exchange-based dark pool of the ASX in June 2010 and the reduction of ASX trading fees on 1 July 2010. In the first-stage regression, dark trading is shown to increase significantly after both market structure changes although the effect of the removal of the ten-second rule is more substantial. In the second-stage regression, the fitted value of dark trading has a significant and positive effect on firm default risk, which suggests a causal effect of dark trading on firm default risk. Given that the removal of the ten-second rule leads to substantial increase in dark trading, we adopt it as an exogenous event to conduct difference-in-differences tests.

We rank all sample firms based on their changes in dark trading surrounding the event for the treatment (control) group that experience the most (least) change in dark trading. We then use propensity scores estimated from a probit model to match firms in the two groups by the closest propensity score matching, so that the matched treatment and control groups have similar firm characteristics and level of dark trading before the exogenous event. In both treatment and control groups, firm default risk drops substantially from 2008 to 2010, which is consistent with the onset of the Global Financial Crisis (GFC) in 2007-2009 and the improved firm creditworthiness following this event. The difference-in-differences test shows that firms in the treatment group experience a much weaker reduction in default risk around the exogenous event in 2009 compared to firms in the control group, which supports a positive causal effect of dark trading on firm default risk.[12] Our findings remain robust in the difference-in-differences regressions where control variables and industry fixed effects are further controlled for.

In our first study of firm valuation, we show that dark trading has negative impacts on firm valuation. Since poorer performing firms are more likely to default, the positive relationship between dark trading and default probability could simply be a direct result of the firm value effect. To address a mechanical relationship between firm value decreasing and, therefore, default risk increasing, we adopt additional tests to control for the effect of firm value in both baseline specifications and difference-in-differences regressions, and the positive effect of dark trading on firm default risk remains significant. It demonstrates that the positive relationship between dark trading and firm default risk is not mechanical through the reduced firm value.

[12] As shown in the difference-in-differences regressions reported in Panel F of Table XVII, the coefficient of *AFTER* is significantly negative. It indicates that both treatment and control groups have decreased default risk in 2010 (i.e., after the exogenous event in 2009), which is consistent with improved firm creditworthiness after the Global Financial Crisis. The treatment (control) group experience the most (least) increase in dark trading activities following the exogenous event. The coefficient of *TREAT×AFTER* is significantly positive, showing a smaller reduction in default risk for the treatment group compared to the control group (i.e., a positive effect of dark trading on firm default risk).

As discussed above, dark trading could increase firm default risk through four possible mechanisms, i.e. through reducing stock liquidity, reducing information efficiency, increasing blockholder ownership, and/or increasing financial constraints. We further adopt difference-in-differences tests to examine the underlying mechanisms, and document a causal effect of dark trading on reducing stock liquidity and increasing blockholder ownership; however, there exists weak (little) evidence of dark trading affecting information efficiency (financial constraints). It suggests stock liquidity and blockholder ownership are the underlying mechanisms for dark trading that affect firm default risk. To understand their relative importance, we compare the two mechanisms through a horse race following Brogaard, Li, and Xia (2017), and find that the stock liquidity channel better explains the effect of dark trading on default risk.

After testing the underlying mechanisms, it remains unclear whether there exists a residual or direct effect of dark trading on firm default risk. In addition, the effect of dark trading on reducing firm value could partially explain the effect of dark trading on increasing firm default risk since firms performing badly are more likely to default. Following He and Tian (2013), we disengage the direct versus indirect effect of dark trading on firm default risk in the framework of difference-in-differences regressions. We find that the underlying mechanisms together with firm value can explain up to 17.75% (22.61%) of the total effect of dark trading on the one-year (five-year) expected default frequency, and a significant residual or direct effect for dark trading to affect default risk also exists. It demonstrates a novel role of dark trading in affecting firm default risk, which goes beyond the underlying mechanisms and the influence of dark trading on firm valuation.

This study contributes to the growing literature that examines the impacts of dark trading. Different from existing studies that focus on various aspects of market quality (see, e.g., Buti, Rindi, and Werner, 2011; Degryse, de Jong and Kervel, 2015; Foley and Putninš, 2016), it tests the long-term real effects of dark trading in affecting firm default risk. We document an undesired consequence of increased dark trading in terms of increasing firm default risk, and the channel of stock liquidity has the highest explanatory power. It complements Comerton-Forde and Putninš (2015) that show a detrimental effect of dark trading on stock liquidity in the Australian market, although we adopt firm-year observations and examine the long-term effect instead. We demonstrate that the reduced stock liquidity caused by increased dark trading could make firms more likely to default, and there exists a significant residual and direct effect of dark trading on firm default risk. On the other hand, we find little impact of block trading on firm default risk. Despite having limited pre-trade transparency, block trades are managed by upstairs brokers and have much less non-execution risk compared to dark trades. Our results support the existing literature on the minor impact of block trading on market quality and corporate information environment (see, e.g., Comerton-Forde and Putninš, 2015). Our findings also provide new insights into the determinants of firm default risk by demonstrating that dark trading activities affect expected default frequency of various horizons.

While ample evidence exists that firm default risk is associated with firm fundamentals (Bharath and Shumway, 2008), managerial shareholdings (Shuto and Kitagawa, 2011), corporate governance (Schultz, Tan, and Walsh, 2017), and CEO compensation structure (Mann, 2005), less is known about how investor trading activities affect firm default risk. Although corporate debt structure has been linked to trading in CDSs (Chen, Saffar, Shan, and

Wang, 2018) and options trading (Cao, Hertzel, Xu, and Zhan, 2020), this study is the first that documents stock trading activities in dark pools exerting influence on firm default risk. Gharghori, Chan, and Faff (2009) argue that the Australian market is riskier than the U.S. market due to the high concentration on resource companies, and therefore the investigation on default risk is much more likely to be observed in Australia. Due to the availability of a single consolidated source of trading records, the Australian market is an ideal venue for understanding real effects of dark trading, and our study also contributes to Australian studies on dark trading (see, e.g., He and Lepone, 2014; Foley and Putninš, 2014; Comerton-Forde and Putninš, 2015; Foley and Putninš, 2016). By revealing a real effect of dark trading in increasing firm default risk, we suggest examining the risk implications when making regulatory changes about dark trading.

1.4 Structure of the Thesis

This thesis is structured into five chapters. Chapter 1 introduces the topic covered by the whole thesis. Chapter 2 explains the institutional details and background of dark trading. The difference between dark trading and block trading is also discussed in this chapter. Chapter 3 discusses the literature reviews and hypothesis development. Chapter 4 provides details on sample selection and research design. Chapter 5 presents the first empirical study that examines the impacts of dark trading and block trading on firm valuation. Chapter 6 discusses the results of the second empirical study for the impacts of dark trading and block trading on firm default risk. Chapter 7 concludes the thesis.

Chapter 2

Institutional Details and Background

In this chapter, we discuss the institutional details and background of dark trading and block trading. Section 2.1 elaborates the definitions, characteristics, and execution process of dark trading. Different types of dark pools are discussed in Section 2.2. The advantages and disadvantages of using dark pools are described in Section 2.3. In Section 2.4, we distinguish dark trading from block trading and discuss their similarities and differences. Finally, Section 2.5 provides details on dark trading in Australia and the differences between the dark pools in the U.S. and Australia.

2.1 Dark Trading and Dark Pools

The traditional stock exchange markets (hereafter called lit markets) are operated with opened limited order book, which exposes pre-trade information to the public. All the market participants can see the order details, such as order type and volume, on the limit order book. When limit orders are submitted to the lit markets, they are immediately visible to all market participants, and such information release could have immediate price impact (e.g., Hautsch and Huang, 2012). For this reason, lit orders are executed with pre-trade transparency.

In contrast, dark orders are not required to be displayed to other participants before execution. The trading details are reported after execution only, and therefore dark orders have the potential to minimize market impact costs. While limiting the ability of other participants to identify the order details and to trade ahead, dark orders help to prevent trading against the interest of the order maker and provide no pre-trade transparency benefits to the participants.

Dark pools were formed as the private matching venues originally and dark liquidity refers to buy and sell orders that are not visible to the rest of the market. In particular, a popular broker may receive many buy- or sell-side orders from his/her clients. If there exist buy and sell orders of the same size and on the same stock, the broker does not need to send orders to the exchange and instead executes the two orders directly, which saves transaction fees that would have been charged by the public stock exchange. Consequently, the broker becomes a private matching "venue" with additional non-displayed "dark liquidity" provided to the investors. However, such dark liquidity does not necessarily benefit investors since the non-execution risk introduced and the execution time are delayed.

Nowadays, dark trades are executed away from lit markets and in the venue called dark pools or crossing networks (named as CNs). Generally speaking, dark pools are trading venues without publicly disseminated bid and ask quotations (Degryse, Tombeur, Van Achter, and Wuyts, 2013). Based on the definitions from ASIC Review (ASIC, 2013), dark pools/venues are electronically accessible pools of liquidity that are not pre-trade transparent, including crossing systems and dark venues operated by exchange market operators. A crossing system is an automated service provided by a market participant to its clients that matches or executes client orders with orders of the market participant (i.e. against the participant's own account) or with other users with orders in the system and these orders are not matched on a pre-trade transparent order book. The market participant is defined as a participant of a licensed market, with permission to directly access the market to trade on behalf of their clients and/or themselves.

In the traditional exchange markets, investors have access to the opened limit order book and therefore order placement can trigger a price impact on the market. The emergence of high-frequency trading (HFT) has changed the execution method in lit markets. With the development of computerized algorithmic trading, high frequency traders could send flash orders in millisecond to the market, and HFT has flourished worldwide in recent years.[13] From 2012 to 2015, the level of HFT in equity markets remains reasonably steady at 27% of total turnover in Australia (ASIC, 2015). By using an automatic trading algorithm and high-speed technology, high frequency traders benefit from what are called "front-running scalping strategies".[14]

Originally, the process of HFT was simply implemented by spreading detecting tools that learned the order book depth and posted on the best bid or ask, before the market price of the stock quickly moving to the other side (Patterson, 2012). By using high-speed market data and developed algorithms, modern HFT scalping strategies evolved and manipulated the electronic exchanges. The aim of HFT scalping strategies is to gain a favorable queue position—any particular scalping strategy must have a high probability of entering the trade and an equally high probability of either exiting for spread or, if the spread cannot be gained, of immediate exit to avoid losses (Manahov, 2016a). The mechanism of "front-running scalping strategies" mostly involves stepping ahead of the supply and demand imbalances, which are present in the

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[13] High frequency traders use different computer algorithms to execute trading orders at super speed (Goldstein, Kumar, and Graves, 2014). The trading speed of HFT could be as fast as microseconds (millionths of a second) and even nanoseconds (billionths of a second). Based on the argument in Manahov (2016b), recent sophisticated HFT algorithms could execute 40,000 round-trip trading orders (e.g., buys and sells) at the speed of a human eye blink.

[14] The "front-running scalping strategies" use high speed computer to jump the queue of the quotation. The trading is based on market information and follows market regulations. HFT is legally and well developed around the world. Nevertheless, it may create a flash crash in the market and regulators worldwide are still working on the normalization of HFT.

market depth, and getting profits on the better price they have (Bodek, 2013). HFT scalping strategies are predatory in their aim of stepping ahead of institutional order flows, violating the price-time priority and making it significantly more difficult to fulfill lit orders in the expected way. The profits of HFTs are generated by using such strategies (Baron, Brogaard and Kirilenko, 2012; Brogaard, Hendershott and Riordan, 2014; Hirschey, 2019; Lee, 2015; Manahov, 2016a). These kinds of predatory quote stuffing strategies generate \$1.5–\$3 billion in annual profits in the U.S. equity market alone (Narang, 2013), and potentially increasing systemic risk (Goldstein, Kumar and Graves, 2014).

To avoid the predatory trading by high frequency traders, non-high frequency traders need a market without pre-trade transparency. Dark pools were created based on the demand of brokerages to execute orders confidentially without information leakage before execution. However, because dark pools are much smaller trading venues than lit markets, it is hard for dark pool operators to maintain liquidity without allowing high frequency traders to participate. There are obvious conflicts between high frequency traders and dark pool users. In 2016, the U.S. Securities and Exchange Commission (SEC) and the New York Attorney General's Office (NYAG) filed lawsuits against Barclays Capital Inc. and Credit Suisse Securities (USA) LLC who operate two of the largest U.S. dark pools, alleging they defrauded and deceived investors with inaccurate marketing material about their unregulated dark pools. They were accused of allowing high-frequency trading firms to participate in their dark pools and even favoring HFT over trading counterparts for pension funds, mutual funds and other financial institutions, and their dark pools did not operate as advertised. Barleys and Credit Suisse agreed to pay US\$154.3 million combined to settle the allegations, which marked the largest penalties in U.S.

history against dark pools.[15] There have been other dark pool operators charged by the U.S. SEC with misleading dark pool subscribers about market participants, such as UBS Securities LLC, ITG Inc., and Citigroup Global Markets Inc.[16]

To understand the order execution process, Figures I and II illustrate the order submission routes in lit markets and in dark pools, respectively. As shown in Figure I, order submission follows a linear process in lit markets, where clients send orders to brokers in order to reach the exchange. Brokers send the orders to the exchange for them to be executed, and clients pay commission fees to the brokers who are charged transaction fees by the exchange. Such orders are subject to arbitrage strategies from high frequency traders as their details are revealed to the public on the exchange. Figure II illustrates the execution process with the possibility for brokers using the dark pools. When brokers receive orders from clients, instead of sending orders to the exchange they can first try to match orders in their own dark pools with the orders of other clients and their own. There are three advantages for brokers to do so. First, it can save transaction fees charged by the exchange. Second, additional liquidity is added to their operated dark pools. Third, trading in dark pools is protected from being exploited by HFT. In case they could not fill in the orders in their own dark pools, some passive brokers may send orders to the exchange for execution directly. Alternatively, brokers may search outside dark pools that are operated by other brokers to keep the order details confidential, and unfilled orders will be sent to the exchange eventually. The searching process in their own dark pools or outside dark

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[15] The U.S. SEC's press release is available at: https://www.sec.gov/news/pressrelease/2016-16.html.

[16] The U.S. SEC's press releases are available at: https://www.sec.gov/news/pressrelease/2015-7.html, https://www.sec.gov/news/press-release/2018-256, and https://www.sec.gov/news/press-release/2018-193.

venues is called internalization.

Insert Figures I and II Here

2.2 Types of Dark Pools

The inception of dark trading could be traced back as early as the 1970s, formed as the private phone-based crossing networks between buy-side traders. In the following decade, the electronic platforms, such as Posit and Instinet, substituted phone platforms. Banks (2010, p. 3) states: "*A dark pool is a venue or mechanism containing anonymous, non-displayed trading liquidity that is available for execution.*" Compared with lit market liquidity, dark pools provide additional non-displayed "dark liquidity" to the investors.[17]

Dark pools can be classified into different types based on their characteristics, but the classification method varies from study to study (Preece, 2012). For example, a well-established source of dark pool statistics provided by Rosenblatt Securities, an institutional brokerage firm specializing in market structure, categorizes dark pools into four groups: (i) pools operated by bulge-bracket brokerage firms; (ii) pools operated by market makers; (iii) independent or agency pools; and (iv) consortium-sponsored pools. Alternatively, TABB Group, which is a well-known international research and consulting firm, categorizes dark pools into three groups: block-cross platforms, continuous-cross platforms, and liquidity-provider platforms. Based on the characteristics of the venue, Mittal (2008) classifies dark

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[17] Dark pools were formed as the private matching venues originally and dark liquidity refers to buy and sell orders that are not visible to the rest of the market.

pools into five different types: public crossing networks, internalization pools, ping destinations, exchanged-based pools, and consortium-based pools. The determination factors include ownership, users of the system, price and order determination, liquidity type and level, average trading size, accessibility, partners in liquidity issues, and the price indication method.

Public crossing networks are agency-only trading venues set up to exclusively generate commissions. They are usually established and operated by broker agencies who have direct connections to buy-side traders. Proprietary orders are not submitted by the operators and there is no provision of liquidity on their own. As a result, conflicts of interest might arise between operators and their clients.

Internalization pools aim to internalize the operator's trade flows, focused on cost reduction via in-house processing of client orders. Besides retail orders, these pools could include proprietary order flow from the operator. Buy-side traders can access the pools, but the operator can decide whether to allow sell-side traders to have any access. Similar to public crossing networks, internalization pools require a high level of liquidity to generate economic value. However, their methods of attainment are very different. Public crossing networks depend on external participants, while internalization pools depend on internal traders' liquidity.

Ping destinations are usually operated by hedge funds or electronic market makers, which can be seen as outliers compared to other types of dark pools.[18] They only accept immediate-

[18] Usually, ping destinations are single-dealer platforms. Unlike traditional dark pools, they allow the brokers to query third parties regarding a client's order that could fill the order at a tailored price. In addition, they face fewer transparency requirements than traditional dark pools. The U.S. SEC requires dark pool operators to disclose to clients how their platforms operate and who are the other participants trading on the platform. However, this requirement is not applicable to ping destinations. Source: Bloomberg.

or-cancel orders (IOC orders), and therefore it is impossible to place orders on a long-term basis.[19] The restriction on IOC orders leads either to a direct execution or the order being deleted. Such a rapid order is called a "ping", from which the name of this category is derived. Another characteristic of these dark pools is that their clients' order flow interacts only with the operator's flow. In other words, the trading activities are limited exclusively between the operator and its clients.

Exchanged-based pools are registered by exchanges. They aim to improve the liquidity of an existing exchange market and their formation of execution is the same as the exchange.[20] Exchange-based dark pools have emerged around the world. For instance, the International Securities Exchange's (ISE) MidPoint Match Platform was launched in 2006, while the New York Stock Exchange's (NYSE) dark pool is called MatchPoint and started operations in 2008. In Australia, Centre Point launched in 2010 the first exchange-based dark pool operated by the ASX. Chi-X hidden is another exchange-based dark venue launched by Chi-X in 2011. In general, exchange-based dark pools can be accessed by sell-side traders.

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[19] An Immediate-Or-Cancel (IOC) order requires all or part of the order to be executed immediately, and any unfilled parts of the order are canceled.

[20] In the stock market, a best bid is the highest price a buyer is willing to pay, whereas a best offer is the lowest price a seller is willing to sell. Dark pools use the best bid and best offer to match orders. Usually, the average price of the best bid and the best offer available on an exchange market is used to match a trade in dark pools. Consequently, both the buyers and sellers who trade in dark pools could have a better price compared to trading in the displayed exchange market. The formation of execution in exchange-based dark pools is the same as the formation of execution in the exchange market. For example, ASX Centre Point describe the execution formation as "*Non-displayed liquidity matched at the mid-point or other permitted price step inside the National Best Bid and Offer (NBBO)*". Available at: https://www.asx.com.au/services/trading-services/asx-centre-point.htm

Consortium-based pools are jointly operated by several brokers, usually an association of several institutional traders. They are formed like a hybrid of public crossing networks and internalization pools. The partnered operators first try to match orders in their own dark pool and send only unexecuted orders to the consortium pool, and they benefit from the low transaction cost.

2.3 Advantages and Disadvantages of Dark Pools

Dark trading supporters contend dark pools are more reliable markets, especially when compared to public exchanges. Providing pre-trade anonymity is described as the core business of dark pools, which enables their users to hide their information. In dark pools, investors can have their orders executed without exposing their trading strategies. Compared with sending orders in the lit market, investors are less worried about any price movement caused by information leakage in dark pools.[21]

The other advantage of using dark pools is the much lower execution fee of dark trading.[22] Apart from the decreased market impact costs, the commission saving directly benefits participants. Without routing the orders to the lit markets, dark pools eliminate the transaction costs charged by the exchange. In some dark pools, for example ping destinations, clients' orders are only executed against the pool operator's own orders. In the case of using

[21] Sending orders into dark pools mitigates speculation since the information can be treated confidentially (Comerton-Forde and Putninš, 2015).

[22] Anticipating the entry of Chi-X Australia, the ASX reduced its trading fees on 1 July 2010. After (Before) 1 July 2010, lit market trades were charged at 0.15 bps (0.28 bps), block and portfolio crossing fees were 0.10 bps (0.15 bps), and priority crossing fees were 0.05bps (0.075 bps) (Foley and Putninš, 2014).

internalization dark pools, buy and sell orders are internally matched and not necessarily routed to external markets.

On May 6, 2010, the U.S. market experienced a flash crash which erased almost 1,000 points from the Dow Jones Industrial Average. Trillions of dollars of market value were lost from the crash, although a large part of this loss was recovered within twenty minutes. The joint announcement from the U.S. SEC and Commodity Futures Trading Commission (CFTC) concluded the crash was exacerbated by a lack of proper market circuit breakers or trip mechanisms when a huge number of HFT computers sparked a chain reaction.[23] In particular, high frequency traders sold aggressively to eliminate their positions and withdrew from the markets in the face of uncertainty, which exacerbated the price decline started by a significant decline in the E-Mini S&P futures contracts. Without pre-trade transparency, dark pools restrict HFT and therefore are less prone to flash crashes than lit markets.

While many people advocate the use of dark pools, there have been concerns raised as well. Dark pools have a high level of non-execution risk and it would be harder for orders to be executed in dark pools than in lit markets. As a result, the benefits of using dark pools, such as saving in commission fees, would be offset by the high level of non-execution probability (Keim and Madhavan, 1998; Gresse, 2006; and Zhu, 2014). Another concern is the exclusiveness in dark pools. In contrast to public exchanges which are accessible to all traders, some dark pools limit access to specific traders. Access depends on whether the trading rule in a specific dark pool admits institutional investors, broker-dealers, high frequency traders, and specific execution algorithms (Boni, Brown, and Leach, 2013). The exclusiveness of dark pools

[23] Available at: https://www.sec.gov/news/studies/2010/marketevents-report.pdf.

can be particularly detrimental to liquidity supplier who are prohibited from large dark pools. On the other hand, inconsistent rules of dark pools produce unnecessary information and liquidity fragmentation. Traders and regulators are concerned about problems arising from the fragmentation: more difficulty in searches and exclusivity of information.

In addition, dark trading can hinder price discovery without pre-trade transparency. Even though dark pools often release post-trade information either voluntarily or to meet regulations, the released information is neither universal nor easy to verify (IOSCO, 2010).[24] Thus, the absence of pre-trade information and incomplete post-trade information make it harder to establish an accurate price quote for a security (ASIC, 2013). Given the rapid growth in dark pools, opponents argue that as more dark pools handle a larger proportion of orders, the price derived from available information becomes less representative of the true price. Having accurate prices is necessary for resource allocation and efficiency, and consequently there is a negative impact of dark pools on price discovery which has prompted academic research (Comerton-Forde and Putninš, 2015).

2.4 Differences in Dark and Block Trading

Generally speaking, dark trades can be divided into block dark trades and non-block dark

[24] IOSCO (2010) states: "*The Technical Committee notes that dark pools in many jurisdictions are already required to publicly disclose information about executed trades. This information does not, however, necessarily identify the trading venue on which the trade was executed. Regulators should consider whether it is appropriate to require the identity of the dark pool operator to be revealed and, if so, how (e.g. trade by trade and real time; trade by trade and end of day; or end of day and aggregate volumes in individual stocks).*" Available at: https://www.iosco.org/library/pubdocs/pdf/IOSCOPD336.pdf

trades based on the size of the order. Following Comerton-Forde and Putninš (2015), we refer block dark trades as block trades and non-block dark trades as dark trades in this thesis. Both block trades and dark trades publicize little information before execution, and the trading reports will be sent to the CLOB after execution in a delayed period of time based on local regulation requirements. Although block trades and dark trades both have no pre-trade transparency and are executed outside of exchange markets, they are different in several aspects. The first difference is the size requirement. Dark trading has no minimum size restriction but there exists a minimum value per trade requirement for block trade.[25]

Second, block trading has a longer history than dark trading. Before dark trading was introduced, block traders negotiated prices with brokers outside the limit order book quotes in the market called the "upstairs market". As the name "upstairs" implies, the negotiation process is done outside the exchange market, and the negotiating details are not known to the public. The original idea of launching dark trading was to facilitate block orders. Regulators want to offer more liquidity to block traders. Using Australia as an example, in the 2013 and 2015 reports of ASIC, they emphasized that "*…the original purpose of the introduction of dark order types was to facilitate large orders and to manage their market impact…*". Dark trades are emerging in recent years as a result of the development in systematic matching technology.

The third difference between dark trading and block trading is the negotiating process. In the "upstairs market" for block trading, the seller and buyer could negotiate the details, for example, the execution price of trade privately. Dark traders place their orders in dark

[25] Commencing in May 2013, the minimum block trade size has been reduced from AU$1 million to AU$200,000 for the vast majority of securities in Australia.

pools/venues operated by exchanges or brokers instead. The first Australian exchange-based dark pool is called Centre Point and was launched by ASX in January 2010. It executes orders based on time priority at the midpoint of the bid-ask spread on the CLOB. Although broker-operated dark pools have their unique execution rules, dark orders are required to be settled at or within the prevailing best bid or ask price. In dark pools, it is impossible for the counterparties to negotiate with each other. Madhavan and Cheng (1997) argue that by negotiating upstairs block trades are more likely to give public a signal of trading motivation, and therefore upstairs block trading has greater pre-trade transparency than lit-market trading.

2.5 Dark Pools in Australia and Other Countries

Dark pools have emerged and grown rapidly in recent years around the world. For example, the share of dark trading in the U.S. consolidated volume has grown from 17% in July 2008 to 37% in June 2014 (Rosenblatt Securities, 2015). Dark pools have also been very successful in attracting order flows. They account for approximately 15% of consolidated volume in the U.S. (Rosenblatt Securities, 2013), 10% in Europe (Thomson Reuters, 2013), and 14% in Australia (ASIC Report, 2013).

In Australian equity markets, dark liquidity has remained reasonably constant at around 25–30% of total turnover since 2010 and until the September quarter of the 2012 block , while dark trades represent 24.8% of total volume in Australia (ASIC, 2013).[26] The proportions of block trading are larger than dark trading, although the difference is not substantial (58% in

[26] The largest proportion of executed trading is still in the exchange market. The lit volumes contribute 61.7%. in Australia while the remaining 13.5% is from auctions (ASIC, 2013).

block trades vs. 42% in dark trades). From 2005 to 2015, the numbers of operating dark venues rose dramatically. Specifically, in 2005 there was only one dark venue in Australia while the number increased to 18 in 2015. Appendix I shows details of the venues and number of operators in each year.[27] In addition to the broker-operated dark pools, both ASX and Chi-X Australia provide mechanisms for executing dark trades. Since its commencement in June 2010, ASX has operated a dark pool named Centre Point. Centre Point is separate from the lit CLOB (lit orders do not interact with orders in Centre Point) and executes orders at the midpoint of the best bid and ask quotes in the CLOB. In contrast, Chi-X Australia does not have a separate dark venue, but instead allows dark order types to interact with lit orders on its market.

Before 31 October 2011, ASX was the only equity exchange market in Australia. The monopoly of ASX ended on 31 October 2011 when Chi-X Australia was granted a financial market license by the Australian Securities and Investments Commission.[28] The ASX is one of the world's top ten equity markets by market capitalization and includes around 2,200 listed companies and around 90 brokers among which the largest 12 brokers account for 80% of equity turnover. Furthermore, most of the top brokers are large global players in the securities industry (Foley and Putninš, 2014).

In Australia, all the exchange orders (or named as lit orders) are matched based on price-

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[27] The numbers of operating venues are calculated by using the number of commenced dark pool venues minus ceased venues.

[28] The Australian Securities and Investments Commission (ASIC) regulates Australia's corporate, markets and financial services. The information regarding Chi-X commencement can be found at: https://www.chi-x.com.au/wp-content/uploads/history/171011%20Press%20Release%20-%20Chi-X%20Australia%20Final%20License%20Approval.pdf.

then-time priority and recorded on CLOB transparently.[29] The orders in the exchange are displayed on CLOB as soon as they have been placed. Both the ASX and Chi-X Australia trade continuously between 10am and 4pm.[30] Unlike the U.S., there are no "trade-through" rules in Australia that require orders to be routed to the market with the best available quote.[31] In Australia brokers have a statutory "best execution" obligation to their clients.

Dark orders and block orders do not need to be recorded when they have been placed. They are not required to interact with the CLOB while providing a delayed report after execution. So literally, dark trading and block trading are the only two trading types without pre-trade transparency.[32] However, because the orders will be reported after execution, the post-trade transparency is similar as exchange market orders.[33]

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[29] The price-then-time priority is the rule used for prioritizing orders in the process of execution. Price is the first ranking criterion for execution. After that, the orders with the same price are ranking by the time they are entering.

[30] The ASX opens trading with a series of call auctions between 10:00am and 10:09am. The market is closed with a call auction that takes place between 16:10 and 16:12 at a random time within a 60 second window. Continuous trading on Chi-X occurs from 10:00am to 4:12pm with no opening or closing auctions. Order entry is only possible from 10:00am.

[31] NASDAQ explains the trade-through rule: "*The Trade Through rule is a 20-year-old rule applied to NYSE-listed stocks that states that when a market receives an order, it cannot execute it at a price inferior to any found on another market. In modern electronic markets where trades are executed in milliseconds, this rule can prevent a broker's ability to meet their "best execution" obligation--because speed provides certainty that the price that is advertised can be accessed.*" The report is available at: https://www.etf.com/docs/Nasdaq_Primer.pdf.

[32] Some studies argue that block trading has higher pre-trade transparency than dark trading (Madhavan and Cheng, 1997). However, block trading still exposes less information before execution than trading on public exchange.

[33] Pre-trade transparency is the information of the orders exposing to the public. The information contains the order types (buy or sell) and volumes of the quotation. Post-trade transparency is the information of the details in

Foley and Putninš (2014) discuss the important differences between the dark pools operated in Australia and those operated in the U.S. First, in the U.S. markets all the dark venues are required to be registered as an Alternative Trading System (ATS). However, dark pools in Australia are not licensed as markets instead operating under the rules of an exchange.[34] Second, the interconnection of dark pools in Australia is lower than in the U.S. In Australia, orders sent to one dark pool are not commonly routed to other dark trading venues, although a small number of agency-only brokers running dark liquidity aggregator businesses. Typically, brokers are trying to execute orders in a single dark pool before sending the orders to the lit market (as called internalization). In Australia, it is also common for brokers to send an order in parts to the lit exchange and a dark pool simultaneously. Third, with the exception of block trades, dark pools in Australia may only match orders at or within the spread at prices that are multiples of the minimum tick size on the exchange or the midpoint of the spread.[35] Finally, the reporting systems in the Australian and the U.S. dark pools are different. In Australia, all dark pool trades must be reported and disseminated to the market immediately, while in the U.S. dark trades are reported to the Trade Reporting Facility (TRF) first and then the consolidated book; it is permitted to have a delay of up to 30 seconds (Nimalendran and

executed transactions. In Australia, ASIC Market Integrity Rules require an immediate report of executed dark trade to the consolidated book (Foley and Putninš, 2014).

[34] Dark pools have a strong connection with the public exchange market in Australia. All the dark pools need to be regulated following the exchange rules (e.g., rules of ASX or Chi-X). A number of dark pools have subsequently become more market-like and built connections to other pools (ASIC, 2013).

[35] Block trading has a negotiating process on upstairs market (which in the ASX is called block trade facility) whereas the prices could be made at any price agreed between counterparties. Further details are available at: https://www.asx.com.au/products/block-trade-facility.htm.

Ray, 2014).

Comerton-Forde and Putninš (2015) point out two benefits of investigating Australian dark pools compared with the U.S. ones. Firstly, there is only one CLOB in Australia, recording all trade types (i.e., lit trades, dark trades, and block trades). As a consequence, the Australian CLOB provides precise records. In the U.S. or other markets there are inconsistencies in time-stamps across different trading venues and in classification of trading types, which lead to inaccurate trading records. Secondly, in Australia retail order flow is almost exclusively executed on the ASX.[36] It is different from the U.S. market where almost all marketable retail order flow is routed to wholesale market makers.[37] In Australia, payment for order flow is not permitted and therefore dark order flow in Australia in more similar to the dark order flow executed in the U.S. dark pools rather than the dark order flow executed by wholesale market makers.

[36] For evidence, in September 2010 there was only 4% of retail order flow executed away from the exchange (ASIC, 2013).

[37] There are differences between brokers and market makers (or called wholesalers). Brokers are intermediaries who have the authorization and expertise to buy securities on an investor's behalf. Market makers help to ensure there is enough volume of trading so trades can be done seamlessly. Representing as a warehouse, market makers centralize stocks and make sure there is liquidity in the market.

Chapter 3

Literature Review and Hypothesis Development

3.1 Literature Review

3.1.1 Theoretical Studies of Dark Trading

Several theoretical studies argue that dark pools do influence information acquisition. Grossman and Stiglitz (1980) show that information acquisition must be profitable in expectation for investors to acquire new information and in other words, informed traders are seeking profits to cover their information acquisition costs. Boulatov and George (2013) compare a lit market and a dark market, and they argue informed traders compete more aggressively for liquidity provision in the dark market. As a result, the bid-ask spread and price impact in the dark market are lower than that in the lit market. Boulatov and George (2013) also argue if informed investors could hide order details in dark pools they can enter and exit transactions at low cost.

Degryse, Van Achter, and Wuyts (2009) find that different types of traders choose trading systems based on their individual requirements. For example, a dealer market, proxied as a traditional market in which traders submit orders to dealer, is preferred to the investors with a high willingness to execute immediately. They argue that the introduction of a crossing network influences the order flow on two sides. On one hand, it results in order creation because patient investors now submit crossing network orders instead of refraining from trade. On the other hand, an order diversion effect occurs. Traders less willing to trade divert from the dealer market to the crossing network. Degryse, Van Achter, and Wuyts (2009) also show the execution probability at a crossing network is endogenous and depends on the status of the venue's order book, the observed order flow, and the expectations about future orders.

Given the development of dark venues, theoretical literature in the field of dark pools investigates the potential impacts of dark trading on market quality.[38] Models are built up for studying the impacts of crossing networks (dark pools) on lit market. For example, Foster, Gervais, and Ramaswamy (2007) investigate the role of volume-conditional order-crossing, an automatically crossing network triggered only when a required minimum volume of shares traded, in coexistence with a continuous-auction market. Their model indicates that if an exchange includes a volume-conditional order-crossing mechanism, market breakdowns could be prevented partially at least, market efficiency could be improved, and additional traders could be attracted.[39] Bolton, Santos, and Scheinkman (2016) propose a model in which investors obtain costly information to identify good assets and purchase the assets in opaque markets (e.g., dark pools). They find that cream-skimming does negatively affect the lit markets.[40]

Buti, Rindi, Weaver (2017) investigate the competition between a dark pool and a transparent limit order book. They show that the set of possible strategies expands when a

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[38] Early studies on segmentation investigate the order flow segment of traders. For example, Admati and Pfleiderer (1988) find that the segmentation of informed and uninformed traders reduces incentives for liquidity providers to participate in informed markets. Madhavan (1995) argues that market fragmentation leads to wider spread, higher volatility and less efficient prices.

[39] Foster, Gervais, and Ramaswamy (2007) assert that the mechanism of volume-conditional order-crossing is naturally more attractive to traders without immediately execution requirement. Although the mechanism and exchange market have combined into a whole system, liquidity is cheaper in this mechanism than in a continuous-auction market.

[40] Cream skimming is a business practice of a company providing a product or a service to only the high-value or low-cost customers of that product or service, while disregarding clients that are less profitable for the company. The model indicates that uninformed traders access asset venue that has been cream-skimmed by informed traders.

limited order book is introduced in the model, while the introduction of a dark pool can attract orders away from a transparent central limit order book.[41] However, using an experimental market framework, Bloomfield, O'Hara, and Saar (2015) find that most market outcomes are largely unaffected by the availability of hidden orders. For instance, the "true" spread (include dark liquidity) remains unaffected although quoted spread almost doubles.

Orders sent to dark pools have the benefits of lowering transaction costs and price impact costs, however, dark traders are facing adverse selection risk (e.g., Brolley, 2014).[42] Given dark pools provide benefits and drawbacks to investors, what is the best trade execution route in the world with lit and dark venues coexisting? The Hendershott and Mendelson (2000) model has a trade-off between the incentives of increasing competition between dark pools and dealer markets, and the potential costs of order flow fragmentation. Trades could differ according to the degree of impatience to trade. Dealer markets offer immediacy to the traders, and therefore investors who seek a quick execution are more likely to use dealer markets. On the other hand, crossing networks benefit traders who like to sacrifice immediacy and certainty of execution by lowering transaction costs. In addition, crossing networks can reduce adverse selection by attracting new liquidity and providing a venue other than the dealer markets for informed trading, and therefore trade-off of adverse selection against lower transaction fees

[41] Compared with the theoretical studies about the relationship between dark trading and price discovery (e.g., Ye, 2010; Zhu, 2014), the model in Buti, Rindi, Weaver (2017) does not show evidence about whether dark markets affect price discovery. Because the model does not address the issue of asymmetric information, authors argue it as a complement in theoretical work on dark trading and price discovery.

[42] Adverse selection is a market situation where buyers and sellers have different information, so that a participant might participate selectively in trades which benefit them the most, at the expense of the other trader.

exists in dark pools. Traders who use the dealer markets as a "market of last resort" can induce dealers to widen their bid-ask spread and lead to more efficient dealer prices.[43]

In line with Hendershott and Mendelson (2000), Yin (2005) argues that liquidity traders still bear some costs in searching for better prices, although dealers provide their own quotes to the public for free. He modifies the implicit assumption of Biais (1993) and de Frutos and Manzano (2002) that liquidity traders in fragmented markets can observe all quotes without any costs. He introduces liquidity traders' costs of searching for a better quote which comprise the time spent on communicating with dealers and other direct costs or opportunity costs related to communication and negotiation with dealers. In addition, this quoting process and accompanied search costs are realistic in fragmented markets. The searching costs have significant impacts on the market participants, no matter how small they are.

Kratz and Schöneborn (2014) model the trade-off between reduced transaction costs and non-execution probability in dark pools. They find that the optimal execution strategy uses both lit and dark venues continuously. Whether dark pool orders over- or under-represent the portfolio size depends on return correlations, and whether trading at lit venue is delayed depends on the liquidity in dark pools. Consistent with the theory of trade-off between cost saving and non-execution risk, Cheridito and Sepin (2014) use simulation experiments to demonstrate that the cost saving in dark pools depends on the execution probabilities within

[43] Hendershott and Mendelson (2000) point out the intermarket competition when both markets coexist. They argue that crossing networks and dealer markets are not mutually exclusive. Investors could take advantage of both markets by using crossing networks first; if the orders could not be executed in crossing networks then they subsequently go to the dealer market. However, this execution route may increase searching cost.

the venue. High execution probabilities in dark pools improve the benefits from reduced implementation cost in the venue.

Dark pools often operate as crossing networks that use a derivative pricing mechanism and allow traders to submit unpriced orders only, and all price discovery takes place in the remaining lit markets (Degryse, Tombeur, Van Achter, and Wuyts, 2013).[44] The increase in dark pools naturally raises concerns about the impacts of dark trading on price discovery. There are theoretical papers which model the impacts of dark pools on price discovery, however the results are inconsistent. By using Kyle's (1985) framework, Ye (2010) models the strategic behavior of informed trader when there is a stock exchange and a crossing network (dark pool). The model shows that informed traders could manipulate the price to wrong direction in the lit market. After price moves to the wrong direction they could get a profit from the crossing network. However, an informed trader does not benefit from the mispricing they created by matching orders in the crossing network, because non-execution probability in the crossing network increases. The best decision of informed traders generates a positive correlation between price impact in the lit market and the non-execution probability in the dark pool. The increase in the fundamental value uncertainty augments non-execution probability. Ye (2010) concludes that crossing networks have higher non-execution probabilities, which harms price discovery.

In contrast, Zhu's (2014) model shows that dark pools improve price discovery but reduce lit market liquidity. He argues that stock exchanges are more attractive to informed traders and

[44] The derivative pricing mechanism used by crossing networks requires a sufficiently informative and well-functioning existing primary market.

dark pools are more attractive to uninformed traders. Specifically, the model shows that informed traders tend to trade in the same direction of the market, so it is harder for them to find counterparties relative to uninformed traders. As a result, in dark pools informed traders face a higher execution risk. Hence informed traders would like to trade in the exchange market while dark pools are more attractive to uninformed traders. Under certain conditions, as more informed traders use exchange markets the price-relevant information is concentrated in the lit market. Consequently, the increase in the number of dark pools improves price discovery.[45]

Recently, Ye and Zhu (2019) investigate how the large informed trader chooses between dark pool and lit exchange market and link dark pool with corporate governance. Their model focuses on studying the behavior of activist shareholders' trading. They find that: firstly, hedge funds execute informed orders in dark pools; secondly, the market share of dark pool increases when an activist trades; and thirdly, the market share increases more if the value of the activist's information is higher.[46]

3.1.2 Empirical Studies on Advantages and Disadvantages of Using Dark Pools

Dark pools prevent price impacts without publicly disseminating bid and ask quotations. Some empirical studies show that dark pools lower trading costs and are beneficial to investors.

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45 Many empirical studies emerged based on the two theoretical papers, however, the results are not consistent. Some empirical papers support Ye's (2010) theory (e.g., Hatheway, Kwan, and Zheng, 2017), while others support Zhu's (2014) model (e.g., Menkveld, Yueshen, and Zhu, 2017).

46 The model in Ye and Zhu (2019) indicate which venue an activist used to obtain a large ownership in a firm before intervening in corporate governance. Although it is not a direct study on the relationship between dark pools and corporate governance, it proves that blockholders are very willing to use dark pools to acquire large ownership in a firm and links blockholders to dark pools.

For example, Conrad, Johnson, and Wahal (2003) investigate three platforms offered to institutional investors including crossing systems, electronic communication networks (ECNs), and traditional brokers. By distinguishing the orders filled by single-mechanism orders (the orders use only one trading system) and multiple-mechanism orders (the orders use more than one trading system), they find that crossing systems have economically significant lower total execution costs than brokers, ranging from 14 to 54 basis points. Ray (2010) studies daily data of 2,869 stocks from three large dark pools: POSIT (an equity crossing system launched by ITG Europe), Liquidnet (a global institutional investment network), and Pipeline (an agency broker offers private equities and options trading systems). He finds that the likelihood of using dark pools increases because of greater cost savings for stocks with higher bid-ask spread. Similarly, Ready (2014) investigates the monthly volume of stock in these three dark pools and finds that dark pool volumes are lower for stocks with lower bid-ask spreads, which is interpreted as evidence of institutional traders routing of the stocks to other venues in order to satisfy soft-dollar agreements.[47]

Although dark trading has lower transaction fees, investors face a high level of non-execution risk (or called counterparty risk). Some studies argue that the incentives of low costs are offset by the high level of non-execution risk. For example, Keim and Madhavan (1998) find that crossing networks consistently have lower transaction costs than stock exchanges.

[47] Soft dollars payment is a method of paying brokerage for their services or research through commission revenue. The opposite payment, which is made through normal payment, is known as hard dollars. For example, an institutional investor would like to pay a broker service fee by combining hard dollars (the actual costs are paid) and soft dollars (an obligation to direct the amount of future trades to the brokerage firm).

They also argue that this advantage is attributed by sacrificing execution probabilities. Similarly, Gresse (2006) investigates the difference in trading costs by using 1,400 mid-cap stocks in two six-month periods of crossing networks in Europe from 2000 to 2011. She finds evidence that in POSIT traders saved around £0.022 to £0.024 per share transaction. However, the decreased transaction costs in dark pools are accompanied by 2 to 4 percent of probability of non-execution risk. She concludes that the savings on costs have to be traded off by the low probability of execution. Næs and Ødegaard (2006) find that the execution risk is driven by adverse selection which leads to higher opportunity costs for unexecuted orders.

The trade-off between transaction costs and non-execution risk has also been documented in Altunata, Rakhlin, and Waelbroeck (2009) through experiments. They find that almost all potential savings from dark pools can be lost by adverse selection or gaming. A simple form of gaming is the same as the theoretical model in Ye (2010), in which the traders first submit orders strategically to the CLOB to manipulate the best bid and ask price. Subsequently, incentives are obtained from trading at impacted prices in a dark pool as the prices in dark pool are referring to the exchange market. On the perspective of market structure in dark pools, Boni, Brown, and Leach (2013) argue that the exclusivity in dark pools influences execution quality.

A recent study by Gkougkousi and Landsman (2017) examines how an abnormal dark market share changes at earnings announcements. They find a statistically and economically significant increase in dark market share in the weeks prior to, during, and following the earnings announcement and the increase is larger for firms with a higher quality of information environment. It is consistent with execution (adverse selection) risk being lower for informed (uninformed) traders in dark venues for firms with a higher quality of information environment.

Opposite to the high non-execution risk in dark trading, researchers find that block trading has lower counterparty risk. For example, after investigating upstairs market of block trading, Bessembinder and Venkataraman (2004) document that upstairs brokers reduce execution costs by tapping into unexpressed liquidity, which is consistent with the theory in Grossman (1992).

3.1.3 Empirical Studies on Dark Trading and Market Quality

Many empirical studies investigate the relationship of dark trading and lit market quality, and the impacts of dark trading on market liquidity and informational efficiency are demonstrated as the two most important factors of market quality.[48] Some studies show that dark trading harms the liquidity and informational efficiency of the exchange market, while some other studies do not find such negative impacts. On one hand, some researchers show that dark liquidity worsens market quality. For example, Blume (2007) notes that dark pools are fragmenting liquidity in equity markets. Weaver (2014) examines the effect of off-exchange trading on market quality. The off-exchange trading sample includes 4,140 U.S. stocks and over 90% of the trades are dark trades. The author finds that more dark trading decreases market depth and increases bid-ask spread, revealing a negative effect of dark trading on market quality.

In line with Weaver (2014), Degryse, de Jong and Kervel (2015) show that the effect of dark trading has a negative impact on market quality. Specifically, by using high-frequency

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[48] Liquidity and informational efficiency are commonly used as proxies of market quality. For example, Muscarella and Piwowar (2001) find that increases in security value are associated with market quality improvements. In their study, liquidity is tested as a factor of market quality. Similarly, Degryse, de Jong and Kervel (2015) test liquidity as a proxy of market quality. For informational efficiency, Bennett and Wei (2006) study the impact of order flow fragmentation on market quality and investigate whether informational efficiency of prices affects market quality.

data the authors investigate the impacts of both dark trading and visible fragmentation on market quality for 52 Dutch large and mid-cap stocks from 2006 to 2009. They use liquidity as a proxy of market quality and show that dark trading is detrimental to liquidity. Besides the negative relationship between dark trading and market quality, they also find there is an inverted U-shape of visible fragmentation on global liquidity. Similarly, Degryse, Van Achter, Wuyts (2008) also show that both visible fragmentation and dark trading reduce liquidity on the local exchange. Kwan, Masulis, and McInish (2015) investigate five types of dark pools and conclude that dark trading has a negative impact on liquidity in exchange market.

By employing proprietary trade-by-trade data for a small set of firms in the U.S. market, Nimalendran and Ray (2014) and Hatheway, Kwan, and Zheng (2017) also document a negative relationship between dark trading and market quality. Nimalendran and Ray (2014) test one of the 32 dark pools in the U.S. and find that algorithmic trades for illiquid stocks are correlated with higher spreads and price impact, as well as contemporaneous trading on the lit venues. In line with Nimalendran and Ray (2014), Hatheway, Kwan, and Zheng (2017) find that dark trading contributes less to price discovery and conclude that dark trading has negative impacts on market quality. Additionally, Foley, Malinova, and Park (2013) investigate dark trading in Canada and find that the introduction of dark trading increases exchange trading costs in Canadian exchange markets.

On the other hand, inconsistently, there are also many papers showing that dark trading does not harm market quality. For instance, Fong, Madhavan, and Swan (2004) find no evidence of a liquidity drain away from the continuous market when traders can trade in a crossing network. Buti, Rindi, and Werner (2011) argue that dark pool activity leads to increased market quality because of higher bid depth and lower bid-ask spreads. They also find that dark pool activity is significantly lower for high volatility portfolios than low volatility portfolios. Gresse (2006) argues that the dark order flow from POSIT does not damage the liquidity of the Stock Exchange Automated Quotation (SEAQ) system, which is the dealer market segment of the London Stock Exchange (LSE). O'Hara and Ye (2011) investigate the volume reported through TRFs (trade reporting facilities mandated by the SEC) as a proxy of off-exchange trading in the United States. They find that market fragmentation reduces transactions costs and increases execution speeds. Farley, Kelley, and Puckett (2018) find that dark trading has no significant impacts on market quality after testing a natural experiment (an exogenous shock to dark trading that caused 34% reduction in dark trading volume).

In the fixed income market, Fleming and Nguyen (2013) study the workup protocol, a unique trading feature in the U.S. Treasury securities market that resembles a mechanism for discovering dark liquidity. They find that a dark pool generally contains less information than its transparent counterpart. The authors suggest that workups tend to be used more as a channel for liquidity providers to guard against adverse price movements than as a channel to hide private information.

He and Lepone (2014) investigate the liquidity and execution probability in Centre Point, an Australian exchange operated dark pool. They conclude that the trading in Centre Point has no detrimental effects on market quality. Additionally, Foley and Putninš (2016) test the effects of dark trading in Canada and Australia. They find that dark limit order markets increase market quality, reduce spreads (quoted, effective, and realized) and increase informational efficiency.

Comerton-Forde and Putninš (2015) investigate the relationship between dark trading and price discovery by using Australian sample. They find that dark trades and block trades have different effects on informational efficiency. Their results indicate that a high level of dark trading reduces informational efficiency while low levels of dark trading are benign or even beneficial to informational efficiency. However, there is no evidence shows block trading has significant impact to informational efficiency. In line with Comerton-Forde and Putninš (2015), Brogaard and Pan (2019) find there is no statistically significant effect of dark trading on informational efficiency by studying a sample in the U.S. market, although dark trading improves the price informativeness of stock prices.

3.1.4 Effects of Trading Activities on Firm Valuation

Firm performance is shown to be affected by corporate governance structure (Henry, 2008; Ammann, Oesch, and Schmid, 2011), institutional ownership (Duggal and Millar, 1999; Cornett, Marcus, Saunders, and Tehranian, 2007), stock market liquidity and informational efficiency of the firm (Fang, Noe, and Tice, 2009). Meanwhile, trading activities and investment decisions could also greatly affect firm valuation. Kraakman (1991) argues that insider trading reduces corporate value. In line with Kraakman (1991), Masson and Madhavan (1991) also find evidence that insider trading is harmful to firm value, although firms with greater executive stock ownership are shown to have higher valuation. Dushnitsky and Lenox (2005) examine the effects of investing in corporate venture capital on firm valuation and find that corporate venture capital investment increases firm value.

Individual investor trading is also demonstrated to have impacts on firm valuation. Kaniel, Liu, Saar, and Titman (2012) show that the abnormal returns on and after earnings announcement dates could be explained by aggregate individual investor trading, and around half of the post-announcement abnormal returns are corresponding with private information. Wang and Zhang (2015a) investigate the effect of individual investor trading on stock market liquidity. They demonstrate that stock liquidity is improved by individual investor trading. By using a proprietary data of NYSE retail trading, Wang and Zhang (2015b) find firm valuation is positively impacted by individual investor trading.

Trading in derivatives products could influence firm value as well. For instance, Roll, Schwartz, and Subrahmanyam (2009) investigate the relationship between option trading activities and firm valuation from 1996 to 2005 in the U.S. market. They find that firms with more option trades have higher firm value and the positive effect is stronger for firms with greater informational efficiency. Narayanan and Uzmanoglu (2018) test the movement of firm value affected by trading in credit default swaps. They find that firm value decreases with credit default swap initiated.

3.1.5 Effects of Trading Activities on Default Risk

Default is among the most disruptive events in the life of a firm. Early studies model firm valuation in the presence of default risk (see, Modigliani and Miller, 1963; Stiglitz, 1969; Smith, 1972; Baron, 1974; Baron, 1975; Hagen, 1976). The relationship between stock returns and default risk is also investigated, however, the results are not consistent. Some studies find that default risk have negative impacts on stock returns (Dichev, 1998; Campbell, Hilscher, and Szilagyi, 2008; Gharghori, Chan, and Faff, 2009) while others suggest the opposite (Vassalou and Xing, 2004; Garlappi, Shu, and Yan, 2008; Chava and Purnanandam, 2010). [49]

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[49] Researchers attempt to explain the inconsistent results on the relationship between default risk and expected return. For example, Chava and Purnanandam (2010) argue that the negative relationship between default risk and

Theoretically, there are many models developed to price diversifiable default risk (e.g., Jarrow, Lando, Yu, 2005; Ericsson, Reneby, and Wang, 2015). Meanwhile, some models are built to value derivatives with default risk (e.g., Cooper and Martin, 1996), such as forward contracts and swaps with default risk (e.g., Jordan and Morgan, 1990; Cooper and Mello, 1991) which are linear derivative products, and non-linear derivatives like options under default risk (e.g., Johnson and Stulz, 1987; Hull and White, 1995).[50]

There are many studies examining the determinants of a firm's default risk (see, e.g., Bakshi, Madan, and Zhang, 2006; Ericsson, Jacobs, and Oviedo, 2009; Furfine and Rosen, 2011). Studies on default risk document that stock liquidity do influence default risk. On one hand, some analyses argue that enhanced liquidity increases default risk because of greater firm mispricing and higher volatility from exacerbated noise trading (Baker, Stein, Wurgler, 2003; Goldstein and Guembel, 2008; Ozdenoren and Yuan, 2008; Polk and Sapienza, 2008). On the other hand, two kinds of principles are developed to argue that increased liquidity decreases default risk: "reliance on debt" and "repayment on debt". According to the argument of "reliance on debt", stock liquidity may mitigate default risk by reducing a firm's reliance on debt financing. In particular, stock liquidity reduces the cost of equity (e.g., Lipson and Mortal, 2009), thus making the equity a cheaper source of finance. Because equity and debt are the two

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expected returns in prior studies is caused by the impropriate estimations of expected returns where noisy ex post realized returns are used to estimate expected returns. Using ex ante estimates based on the implied cost of capital, Chava and Purnanandam (2010) find a positive relationship between default risk and expected returns.

[50] Derivatives could be divided to linear derivatives and non-linear derivatives based on whether payoff changes with time and space (in other words, whether the payoff is a non-linear function). Literally, linear derivatives include future, forward, and swap, and non-linear derivatives include others.

major methods of finance (see, Modigliani and Miller, 1958; Modigliani and Miller, 1963), firms with more equity finance are less concerned about debt repayment, as a result, default risk is reduced. By investigating the data of 75 Australian companies in 1994, Collett and Hrasky (2005) find voluntary disclosure of corporate governance information is positively associated with the intention to raise equity capital, but not with the intention to raise debt capital. The results indicate that better governed firms have more equity in the capital structure and are thus less likely to default.

According to the argument of "repayment on debt", stock liquidity reduces default risk by increasing the ability of a firm to raise external finance to pay for debt at the maturity. When a firm have debt obligations default risk is introduced as the probability that a firm's cash flows are insufficient to serve the contractual interest or principle at maturity. Therefore, the ability of the firm to repay debt depends on stock liquidity. In other words, when a firm needs external funds to repay debt before maturity, stock market liquidity is a key factor. Consistent with the "repayment on debt" argument, Frino, Jones, and Wong (2007) show that in the ASX the stock liquidity (measured by bid-ask spread) of firms widens substantially - up to seven months prior to default. This outcome also indicates the likelihood of significant information asymmetries across market participants in the defaulted firms. Additionally, a recent study by Brogaard, Li, and Xia (2017) highlights that default risk falls with an increase in stock liquidity and proposes two mechanisms through which stock liquidity reduces firm default risk: improving stock price informational efficiency and facilitating corporate governance by blockholders. Of the two mechanisms, the informational efficiency channel has better explanatory power than the corporate governance channel.

3.2 Hypothesis Development for the Study of Firm Valuation

In this section, we discuss the hypothesis development concerning the impacts of dark trading and block trading on firm valuation. This study is motivated by the growing literature that examines the impacts of various trading activities on firm valuation, including insider trading (Masson and Madhavan, 1991), option trading activities (Roll, Schwertz, and Subrahmanyam, 2009), individual investor trading (Wang and Zhang, 2015b), and trading activities of Credit Default Swaps (CDSs) (Narayanan and Uzmanoglu, 2018). Despite the rapid growth of dark trading, prior literature mainly focuses on its impacts from the perspective of market microstructure. This study is the first one that examines the valuation effect of dark trading and block trading.

3.2.1 Dark Trading and Decrease in Firm Value

In the literature, dark trades are documented to have detrimental effects on several aspects of market quality. First, although dark pools often have lower transaction costs than lit markets, it can adversely affect trading costs on lit markets. For example, Foley, Malinova, and Park (2013) find dark trading increases trading costs in Canadian lit markets. Hatheway, Kwan, and Zheng (2017) argue that the flight of liquidity from lit markets to dark pools reduces price discovery and increases transaction costs for all markets. Second, dark trading can harm stock liquidity on lit markets (Blume, 2007; Nimalendran and Ray, 2014; Degreyse, de Jong, and Kervel, 2015). Weaver (2014) finds that dark trading in the U.S. is associated with wider spreads, higher price impacts and higher volatilities. Third, dark trading can increase adverse selection risk on lit markets (Comerton-Forde and Putninš, 2015). Ray (2010) finds that the use of dark pools increases with information asymmetry and the difficult of disguising informed trading on exchange markets. Taken together, the various costs induced by dark trading could adversely affect firms' market valuation. For instance, theoretical and empirical studies show stock liquidity should be priced by the market (see, e.g., Amihud and Mendelson, 1986; Acharya and Pedersen, 2005). Lower liquidity leads to higher expected return and thus lower current stock price and less market valuation for the firm (Wang and Zhang, 2015b). Due to the deterioration in market quality introduced by dark trading, we conjecture it has a detrimental effect on firm value. Our first and main hypothesis is formulated as follows.

Hypothesis 1 (H1): *Dark trading activities decrease firm valuation.*

Stock liquidity is an important factor of market quality and can influence market valuation of the firm. Fang, Noe, and Tice (2009) show that firms with more liquid stocks have better performance as measured by the firm market-to-book ratio, and liquidity improves information content of market prices. By using the setting of Real Estate Investment Trust (REIT), Cheung, Chung and Fung (2015) find a causal and positive effect of stock liquidity on firm value and highlight the corporate governance effect of liquidity. Stock liquidity could benefit a firm's market valuation by reducing the cost of capital (Becker-Blease and Paul, 2006; Amihud, Hameed, Kang, Zhang, 2015). Narayanan and Uzmanoglu (2018) find that firm value declines when CDSs are initiated and the effect is greater when CDS trading activity is higher. They show trading in CDSs lowering stock liquidity as one of the underlying channels to increase a firm's cost of capital, leading to decline in firm value. Given the abundant evidence on the detriment effect of dark trading on stock liquidity (see, e.g., Comerton-Forde and Putninš, 2015; Degreyse, de Jong, and Kervel, 2015), we conjecture stock liquidity as an important channel for dark trading to decrease firm value, and the negative effect of dark trading is more pronounced for stocks with lower liquidity as specified in the following hypothesis.

Hypothesis 1A (H1A): *The negative effect of dark trading activities on firm valuation is stronger for stocks with lower liquidity.*

Recent theorical work by Zhu (2014) predicts that dark trading leads to partial segmentation of informed trading and uninformed traders, and a higher concentration of informed trading in the lit markets could harm firms' information environment.[51] For instance, a substantial decrease in uninformed traders in the lit markets could reduce the profitability of acquiring unique private information (e.g., Kyle, 1985; 1989), hindering price discovery. Zhu's (2014) theoretical predictions are supported by some empirical studies (see, e.g., Comerton-Forde and Putninš, 2015) which find orders executed in the dark are less informed than orders executed in the lit markets. In the corporate finance literature, it is often argued that the existence of information asymmetry drives many corporate decisions. For instance, Myers' (1984) pecking order theory conditions the financing behavior of firms on their levels of information asymmetry. It argues that firms want to finance new investment through internally generated funds, followed by debt and finally equity to minimize the adverse selection costs of external financing. Therefore, information asymmetry could be costly to firms by preventing them from raising cheap external capital and forcing them to make suboptimal investment decisions (see, e.g., Fauver and Naranjo, 2010; Fosu, Danso, Ahmad, Coffie, 2016). Armstrong, Core, Taylor, and Verrechia (2011) find a positive relationship between information asymmetry

[51] Informed traders tend to trade in the same direction and face a higher execution risk in the dark pool compared to uninformed traders. Therefore, Zhu (2014) argues that lit markets are more attractive to informed traders, and dark pools are preferred by uninformed traders.

and firms' cost of capital. Taken together, dark trading could harm firm value by reducing stock price informationally efficiency and thus we expect its effect is strengthened when firms' information environment is poorer. It leads us to consider the following hypothesis regarding information efficiency.

Hypothesis 1B (H1B): *The negative effect of dark trading activities on firm valuation is stronger for stocks with lower informational efficiency.*

Earlier standard models of corporate governance do not consider trading as a method of governance, and they argue that concentrated blockholders attempt to exercise "voice", either through direct intervention including extracting private benefits of control (Laeven and Levine, 2008) or through corporate governance channels, such as voting or activism (Maug, 1998).[52] In contrast to this conventional view, more recent studies such as Admati and Pfleiderer (2009), Edmans (2009), and Edmans and Manso (2011), advance the "threat of exit" as a mechanism enhancing firm value. By taking into account trading costs, Gallagher, Gardner, and Swan (2013) examine the role of institutional trading in influencing firm performance. Fang, Noe, and Tice (2009) also propose blockholder intervention as a possible channel for stock liquidity to positively impact firm value, since low liquidity increases the costs to activists from buying shares and intervening. Given that there is evidence of dark trading increasing trading costs (see, e.g., Foley, Malinova, and Park, 2013; Hatheway, Kwan, and Zheng, 2017) and decreasing stock liquidity (see, e.g., Blume, 2007; Weaver, 2014) in lit markets, dark trading could hinder blockholders from exerting the governance role. On the other hand, dark pools offer alternative

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[52] See Edmans (2014) and Edmans and Holderness (2017) for the reviews on the theory and evidence on the role of blockholders in corporate governance.

trading systems for blockholders to acquire ownership. Brockman and Yan (2009) show a negative relationship between blockholder ownership and firm performance as blockholder ownership increases probability of informed trading and idiosyncratic volatility. Thomsen, Pedersen, and Kvist (2006) find different impacts of blockholder ownership on firm performance in the U.S. and Continental Europe. When firms have higher blockholder ownership, we expect to see a stronger effect of dark trading on firm valuation through affecting blockholders' role of governance. This leads to the following hypothesis of the corporate governance channel.

Hypothesis 1C (H1C): *The negative effect of dark trading activities on firm valuation is stronger for stocks with higher blockholder ownership.*

This hypothesis is also in line with Bharath, Jayaraman, and Nagar (2013) which find that exogenous shocks to liquidity lead to greater increases in firm value for stocks with a higher level of blockholders.

3.2.2 Dark Trading and Increase in Firm Value

Dark trading activities have experienced rapid growth in recent years facilitated by rapid developments in technology and the emergence of dark pools. Prior studies provide abundant evidence on the beneficial impacts of using dark trades. For instance, O'Hara and Ye (2011) argue that the emergence of dark pools leads to more fragmented markets. They find increased market fragmentation reducing transaction costs, improving stock price informational efficiency, and increasing execution speed for NYSE and NASDAQ stocks. The use of crossing networks also results in increased savings on spread-related transaction costs (Ray, 2010). By using a unique U.S. data in 2009, Buti, Rindi, and Werner (2011) find higher dark pool trading activities tend to be associated with lower spreads and lower return volatilities. Using Canadian data and Australian data, Foley and Putninš (2016) show that dark limit order markets can benefit market quality, improving stock liquidity and informational efficiency. Gresse (2006) investigates market competition between traditional exchanges and alternative trading systems in Europe and documents a negative relationship between spread and volume executed in dark pools. He and Lepone (2014) find trading activities on the ASX's operated dark pool increasing best depths on the CLOB. In Zhu's (2014) theoretical model, all informed traders are assumed to have the same piece of private information and uninformed traders tend to prefer dark trades compared to lit trades. Consequently, a larger share of dark trading suggests fewer uninformed traders in lit markets and improved price discovery.[53]

The enhanced information efficiency and improved stock liquidity caused by dark trading activities could result in increased firm valuation. For example, if stock price reveals more information, corporate resources may be allocated more efficiently, leading to increased firm valuation (Khanna, Slezak, and Bradley, 1994). Roll, Schwartz, and Subrahmanyam (2009) show that options trading facilitates information production and is positively associated with firm value. Fang, Noe, and Tice (2009) discover that stock liquidity increases firm value as it improves the information content of market prices. To test the valuation effects associated with dark trades, we formulate the following hypothesis.

Hypothesis 2 (H2): *Dark trading activities increase firm valuation.*

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[53] Zhu (2014) assumes that all informed traders have the same piece of private information and considers it as one of the natural conditions. Without the assumed conditions, dark trading does not necessarily improve price discovery.

If stock liquidity (information efficiency) is the underlying channel for dark trading to increase firm valuation, we expect stock liquidity (information efficiency) to increase with dark trading.

Before intervening in corporate governance, an activist needs to acquire a large ownership stake in a firm, and her information is private until she files Schedule 13D. Ye and Zhu (2019) develop a theoretical model to analyze how this large informed trader chooses between the lit exchange and the dark pool and empirically test the predictions. They find that dark trading activities increase when an activist trades and increases more when the activist's value of information is higher. It suggests that the emergence of dark pools facilitates corporate governance of blockholders and improves firm valuation. Edmans (2009) argues that blockholder ownership forces managers to work better and thus enhances firm performance. Taken together, we conjecture blockholder ownership as an alternative channel for dark trading to increase firm valuation.

In addition, it is worth noting other possibilities for dark trading to increase firm valuation. Fang, Tian, and Tice (2014) contend that higher liquidity results in less future innovation on average, which identifies a channel through which higher liquidity may lead to lower firm valuation. Even if dark trading reduces stock liquidity, it is likely to increase firm valuation through enhancing firm innovation. Consequently, the impact of dark trading on firm valuation is ultimately an empirical question.

3.2.3 Block Trading and Change in Firm Value

Block trading is an old form of dark trading that have a minimum size requirement of transaction. Managed by upstairs brokers, block trading facilitates trades that are difficult to be executed in the CLOB and expands the total available liquidity. Details of block trading are revealed to the market on a post-trade basis, providing additional information about the fundamental value. Without the availability of block trading, these large-sized orders would be sent to the lit market, creating short-term demand and supply imbalances and causing temporary price distortion. Therefore, block trading is not expected to harm price discovery or market quality (Comerton-Forde and Putninš, 2015).

An upstairs block trade has no pre-trade transparency similar to dark trade from the perspective of a trader who participates only in the lit market (i.e., the downstairs market). However, from the perspective of the upstairs market trade counterparty, block trade provides greater pre-trade transparency than a lit trade because upstairs brokers can signal the likely motivation for the trade during negotiation. It consequently reduces adverse selection risk and execution costs for large liquidity-motivated trades in the upstairs market. By examining two block dark pools, Ready (2013) finds a smaller amount of institutional volume in stocks with higher levels of adverse selection. It suggests block trades are less likely to be informed compared to lit trades. Comerton-Forde and Putninš (2015) find no evidence of block trading impeding price discovery. It is possibly due to upstairs block brokers tapping into liquidity that would not otherwise be expressed in the CLOB. They also find mixed evidence about the impact of block trading on stock liquidity. Furthermore, they argue in the upstairs market, a block broker can reduce adverse selection risk for the trade's counterparty by signaling the motivation for the trade. Hence it reduces price impact and avoids the temporary price distortions that would occur in the limit order book (Bessembinder and Venkataraman, 2004). Hatheway, Kwan, and Zheng (2017) show block trades having the lowest market impact costs compared to other trade types. Grossman (1992) develops a theoretical model to investigate the information of upstairs market and illustrates upstairs brokers as information repositories, which is empirically supported by Bessembinder and Venkataraman (2004). In Seppi's (1990) theoretical model, upstairs brokers certify trades as uninformed. Madhavan and Cheng (1997) also find that upstairs markets are preferred by traders who can credibly signal that their trades are not information motivated. Taken together, block trading is expected to exert little impact on market quality and firms' information environment, and it implies there is little relationship between block trading and firm valuation.

3.3 Hypothesis Development for the Study of Firm Default Risk

This section develops the hypotheses for the impacts of dark trading and block trading on firm default risk. Default probability is increasing when a firm's cash flows are less sufficient to cover its debt service costs and principal payments. Prior literature has linked corporate debt structure to trading in CDSs (Chen, Saffar, Shan, and Wang, 2018), and trading in options (Cao, Hertzel, Xu, and Zhan, 2020). It motivates us to investigate how trading activities without pre-trade transparency affect firm default risk.

3.3.1 Dark Trading and Increase in Firm Default Risk

The emergence of dark pools raises the concern about the trade-off between equal access and market quality. In contrast to public exchanges that allow all market participants to place orders, some dark pools seek to restrict the eligible trading population. Based on execution data originating in an exclusive dark pool, Boni, Brown, and Leach (2013) point out the possibility of institutional investors exploited by counterparties in dark pools and such predatory behaviors may have significant social costs. Liquidity is often used as a proxy for market quality. Weaver (2014) notes that dark trading decreases market depth and expands spreads of the U.S. exchange markets including AMEX, NASDAQ and NYSE. Based on Australian data, Comerton-Forde and Putninš (2015) find high levels of dark trading reducing stock liquidity and harming price discovery. Degryse, de Jong and Kervel (2015) show that dark trading decreases the liquidity of market quality for Dutch stocks. By using a comprehensive set of data of U.S. off-exchange trading venues, Kwan, Masulis, and McInish (2015) show that the un-level playing field between dark venues and exchanges increases fragmentation and has a detrimental impact on liquidity.

In the prior literature, stock liquidity is documented to influence firm default risk. For instance, Brogaard, Li, and Xia (2017) find a negative causal effect of stock liquidity on firms' bankruptcy risk through the channels of stock liquidity increasing price efficiency and improving corporate governance by blockholders. Narayanan and Uzmanoglu (2018) reveal that trading in CDSs leads to a deterioration in firms' credit quality and stock liquidity. Both studies indicate that stock liquidity reduces firms' default risk. Given that dark trading activities could deteriorate stock liquidity, we conjecture that dark trading could increase firm default risk by reducing stock liquidity. It leads to the following hypotheses.

Hypothesis 3 (H3): *Dark trading activities increase firm default risk.*

Hypothesis 3A (H3A): *Dark trading activities increase firm default risk by reducing stock liquidity.*

Idiosyncratic risk is often considered as an indicator of asymmetric information. Furfine, and Rosen (2011) find idiosyncratic risk strongly increases acquirer default risk. They argue it consistent with asymmetric information allowing managers to better hide risk-increasing actions from outside shareholders by interpreting these actions as reflecting a random outcome of greater ex ante uncertainty (Dierkens, 1991). In Merton's (1974) structural credit risk model, the equity of the firm is a call option on the underlying value of the firm with a strike price equal to the face value of the firm's debt. It predicts that firm default risk increases with equity volatility (Bharath and Shumway, 2008). As a main contributor to equity volatility, idiosyncratic risk is expected to increase firm default risk. It implies that information asymmetry increases firm default risk. On the other hand, Ye (2010) argues when a dark venue co-exists with a lit venue, it enables informed traders to make large profits in the dark by scaling back the trading aggressiveness in the lit markets. It suggests informed traders executing a considerable share of their trades in the dark and dark trades are relatively informative. All else being equal, more share of dark trading indicates higher level of privately informed trading (i.e., more information asymmetry). Therefore, dark trading can increase firm default risk by changing firms' information environment. Chen, Saffar, Shan, and Wang (2018) document the effects of CDS trading on corporate debt structure and argue corporate information environment is the underlying mechanism. Our hypothesis about the information efficiency channel is formulated below.

Hypothesis 3B (H3B): *Dark trading activities increase firm default risk by reducing stock price informational efficiency.*

Ye and Zhu (2019) find that dark pools facilitate activist traders to get large ownership in a firm and therefore blockholder ownership is likely to increase with dark trading activities. Ashbaugh-Skaifea, Collins, and LaFond (2006) show a negative relationship between blockholder ownership and firms' credit rating. Brockman and Yan (2009) find blockholder ownership increases probability of informed trading and idiosyncratic volatility. Under the agency theory framework of Jensen and Meckling (1979), the separation of ownership and control in the modern corporation raises an information asymmetry problem between management and shareholders. The self-interested behavior leads to increased agency risk which decreases the expected value of future cash flows and increases the volatility of cash flows.[54] Consequently, it increases the default risk in a firm (Ashbaugh-Skaifea, Collins, and LaFond, 2006). We conjecture that dark trading could affect firm default risk through the channel of blockholder ownership as specified below.

Hypothesis 3C (H3C): *Dark trading activities increase firm default risk by increasing blockholder ownership.*

Default is often assumed to occur when market assets fall below a certain boundary, however, Davydenko (2012) find that liquidity shortage can precipitate default at high asset values when firms are restricted from assessing external financing. Financial constraints refer to the extent that firms are constrained in their ability to raise funds externally. A financially constrained firm is more prone to default than an unconstrainted one. In addition, one of the central arguments in Myers' (1984) pecking order theory links adverse selection cost to external financing. Firms with more information asymmetry face higher equity costs when raising

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[54] The self-interested behavior refers to institutional investors monitoring a firm to act in their own interests (in some cases the action is contrary to the firm's benefits). The institutional investors would sell their stocks as soon as they find it difficult to monitor firms through direct intervention and run the risk of expropriation by controlling shareholders (Edmans, 2014; Edmans and Holderness, 2017). This tendency can be stronger for foreign blockholders since they may have information disadvantages (Kang, Chung, and Kim, 2019).

external financing, and they tend to make suboptimal investment, which increases firm default risk (see, e.g., Ryen, Vasconcellos, and Kish, 1997; Drobetz, Grüninger, and Hirschvogl, 2010; Fosu, Danso, Ahmad, and Coffie, 2016, for empirical evidence). Derrien, Kecskés, and Mansi (2016) identify exogenous increases in information asymmetry using the loss of an analyst resulting from broker closures and broker mergers, and find them causing firms' cost of debt increased through the financing channel. Given that dark trading is likely to raise firms' information asymmetry, it could increase firm default risk by making firms more financially constrained. We thus consider financial constraints as a possible channel for dark trading to affect firm default risk.

Hypothesis 3D (H3D): *Dark trading activities increase firm default risk by making firm more financially constrained.*

This hypothesis is also in line with Chang, Chen, Wang, Zhang, and Zhang (2019) who propose CDS trading relieves borrowing firms' financial constraints as a possible channel to promote firm innovation. We, however, conjecture that dark trading could make firms more financially constrained and increase firm default risk.

3.3.2 Dark Trading and Decrease in Firm Default Risk

In the literature, there is evidence of dark trading improving stock liquidity and informational efficiency (see, e.g., Gresse, 2006; Buti, Rindi, and Werner, 2011; O'Hara and Ye, 2011; Foley and Putninš, 2016). Brogaard, Li, and Xia (2017) argue both informational efficiency and corporate governance as channels for stock liquidity to reduce firm default risk, although the informational efficiency channel has higher explanatory power than the corporate governance channel. Therefore, dark trading is likely to reduce firm default risk. On the other hand, evidence exists of dark trading decreasing stock liquidity (see, e.g., Comerton-Forde and Putninš, 2015; Degryse, de Jong and Kervel 2015). Decreasing liquidity can alternatively reduce firm default risk if it hinders noise trading, leading to less firm mispricing and lower volatility (see, e.g., Baker, Stein, and Wurgler, 2003; Goldstein and Guembel, 2008; Ozdenoren and Yuan, 2008; Polk and Sapienza, 2008). Taken together, we reformulate the following hypothesis.

Hypothesis 4 (H4): *Dark trading activities decrease firm default risk.*

This hypothesis is in line with Cao, Hertzel, Xu, and Zhan (2020) who argue that option trading enhances information efficiency and affect corporate debt structure. Although Brogaard, Li, and Xia (2016) show that enhanced stock liquidity decreases default risk, there are hidden costs of stock market liquidity. Bhide (1993) points out that stock liquidity discourages internal monitoring by reducing the costs of "exit" of unhappy stockholders, resulting in impaired corporate governance. Chang, Chen, and Zolotoy (2017) find that stock liquidity increases stock price crash risk. Their further analysis suggests that liquidity induces managers to withhold bad news and the accumulated bad news is released all at one causing a crash. Given the hidden costs of stock liquidity and the mixed evidence on the relationship between dark trading and stock liquidity, it remains an empirical question whether dark trading increases or decreases firm default risk.

In Section 3.2, we develop hypotheses for the effects of dark trading on firm value. Firms with higher market valuation have better performance and are less likely to default. The relationship between dark trading and firm default risk could simply be a direct result of the firm value effect. Even so, the effect of dark trading on firm default risk is not necessarily mechanical as default risk can be nonlinear and depends on several factors other than firm value. Anyway, to address the concern of the possible mechanical relationship between firm value and default risk, we include firm value as a control variable and also adopt a difference-in-differences test to control for the change in firm value around an exogenous shock in the empirical study of firm default risk. On the other hand, firm default risk is closely related to firms' risk-taking behaviors, but increased risk-taking does not necessarily improve or worsen firm valuation. Changes in a firm's information environment can influence its risk-taking strategy and consequently affect default risk. For instance, Vallascas and Keasey (2013) show that information asymmetry leads to an increase in bank default risk via excessive risk-taking by banks. Callen and Fang (2015) find that the positive relationship between short interest and future crash risk is more salient for firms with excessive risk-taking behavior. In addition, information asymmetry enables managers to hide risk-increasing actions from outside shareholders by interpreting them as reflecting a random outcome of greater ex ante uncertainty (Dierkens, 1991). Therefore, it is worth investigating the effect of dark trading on firm default risk even if the relationship between dark trading and firm value is examined.

3.3.3 Block Trading and Change in Firm Default Risk

Block trades are negotiated away from the exchange without pre-transparency. Comerton-Forde and Putninš (2015) show block trades having little impact on information efficiency and the impacts of dark and block trades are different. The relatively low informativeness of block trades is in line with the prior studies which find that upstairs markets tend to be used by traders who can credibly signal that their trades are uninformed (see, e.g., Madhavan and Cheng, 1997; Bessembinder and Venkataraman, 2004). Nimalendran and Ray (2014) find little effect of negotiated block trades increasing bid-ask spread, and for liquid situations block trading even improves stock liquidity. It suggests that block trades are likely to be liquidity driven and help to ease the pressure on the quoting exchanges. Using a comprehensive data of U.S. off-exchange trading venues, Kwan, Masulis, and McInish (2015) find little correlation between spread constrained in the lit markets and market share of block crossing networks. Hatheway, Kwan, Zheng (2017) show that execution of large trades on dark venues reduces the detrimental effect of dark trading. Fong, Madhavan, and Swan (2004) study the effect of block trading on exchange markets and find it benefits all market participants. Taken together, block trading exhibits little impact on market quality or a given firm's information environment, and therefore we expect it to have no relationship with firm default risk.

3.4 Is It Possible for Dark Trading to Have Little Impact on Firm Value and Default Risk?

Although our specific focus is to test whether dark trading harms or improves firm valuation, and decreases or increases firm default risk, it is worth noting the possibility of dark trading having little impact on firm value and default risk. He and Lephone (2014) investigate the ASX's operated dark pool−Centre Point and find dark trading is positively related to quoted spread and best depth, and negatively related to order imbalance and volatility in the CLOB. The execution probability of dark orders increases when dark trading is more active. Overall, they find no evidence of Centre Point trading being detrimental to market quality. Foley and Putninš (2016) examine the effectiveness of regulatory efforts to reduce dark trading in Australia and Canada, and they do not find consistent evidence of dark midpoint crossing systems significantly affecting market quality. Although dark pools have lower transaction costs than stock exchanges, such benefits are largely offset by high non-execution risk of dark trading (see, e.g., Keim and Madhavan, 1998; Gresse, 2006; Næs and Ødegaard 2006). By focusing on small order dark pools, Altunata, Rakhlin, and Waelbroeck (2009) document opportunistic savings in dark aggregators but the savings are almost entirely lost to adverse selection. Brogaard and Pan (2019) find that dark trading wields no impact on information asymmetry. Taken together, there is mixed evidence concerning the effects of dark trading on market quality and firms' information environment. Even if the effects are clear, whether they can be translated to changes in firms' market valuation and default risk is unknown. This thesis can be viewed as an effort to: firstly, differentiate the competing hypotheses; and secondly, understand the real effects of dark trading.

Chapter 4

Sample Selection and Research Design

4.1 Sample Selection and Construction of Dark and Block Trading Variables

Our sample comprises constituents of the All Ordinaries Index (Ticker: XAO) listed on the Australian Stock Exchange (ASX) from 2005 to 2015.[55] The All Ordinaries Index is one of the most commonly followed equity indices in the Asia-Pacific region. It contains the 500 largest ASX-listed companies as measured by market capitalization, which accounts for over 95% of the market value of all shares listed on the ASX.

Our transaction data includes all trades and all central limit order book (CLOB) from the AusEquities database maintained by the Securities Industry Research Centre of Asia-Pacific (SIRCA). All trade types (lit trades, dark trades, and block trades) are required to be recorded in CLOB. Following Comerton-Forde and Putninš (2015), we classify trade types based on recorded flags of trades (i.e., "Qualifiers" variable in the AusEquities database) in order to identify lit, dark, and block trades. Dark trades have three types of flags: Centre Point trades, Centre Point crossings, and Priority Crossings. Block trades have a flag called: Special Crossings. After classifying the trade types, we use dark (block) trading ratio to measure dark (block) trading activities, denoted as *DarkRatio* (*BlockRatio*), which is calculated as the average of daily dark (block) trading ratio that is the percentage of dollar volume of dark (block) trades to the total dollar volume in the stock. In Figure III, we report the yearly average dark

[55] As reported in Appendix I, the first dark venue in Australia was launched in 2005 and the number of dark venues increases in the following years. Therefore, we choose the sample period to start from 2005 to capture the rising of dark trading activities. In the difference-in-difference tests, we consider the years before and after the exogenous event in 2009 (i.e., 2008 and 2010), although the baseline regressions and other endogeneity tests consider the whole sample period of 2005-2015. Our findings remain robust over the entire sample period and the subperiod of 2008-2010.

trading ratio and block trading ratio over the entire sample period. It shows an increasing trend in dark trading activities, while block trading experiences a substantial increase in earlier years but starts to decline from 2012.[56] To account for non-normality concerns, we use natural logarithm of dark (block) trading ratio, *DARK* (*BLOCK*), to measure dark (block) trading intensity in our analysis.[57]

Insert Figure III Here

We collect daily stock price, return, and market capitalization data from Thomson Reuters Datastream database, accounting data and industry information from Thomson Reuters Worldscope database, institutional ownership data from Thomson Reuters Ownership database, and analyst forecast information from I/B/E/S database. We consider two methods of industry classifications in our analysis. The first industry group set (*Industry1*) is constructed based on

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[56] Dark trading and block trading activities are relatively low in the first two years of the sample period (i.e., in 2005 and 2006). In unreported robustness tests, we discard the observations of the first two years and our findings remain robust.

[57] To prevent missing daily observations in the natural logarithm variables for the trading days without dark trades or block trades, we adjust *DarkRatio* and *BlockRatio* by adding a small number, say 10^{-3} or 10^{-10}, before taking the natural logarithm. Comerton-Forde and Putninš (2015) consider log-transforms of the dark and block trading shares as alternative measures of dark and block trading activities. Wang and Zhang (2015) also adopt the natural logarithm of individual trading volume ratio as their measure of individual investor trading. In the study of firm value, we do not apply the logarithmic transformation on other variables except for firm size (SIZE) which is the natural logarithm of market capitalization, following prior studies (see, e.g., Roll, Schwartz, and Subrahmanyam, 2009). In the study of firm default risk, we adopt natural logarithms of market value of equity (*EQUITY*) and face value of debt (*DEBT*) as controls and calculate annual excess return (*EX_RET*) as the arithmetic difference between the stock's annual return and the All Ordinaries index annual return, same as in Bharath and Shumway (2008) and Brogaard, Li, and Xia (2017).

2-digit Global Industry Classification Standard (or GICS) code, and the second industry group set (*Industry2*) is based on General Industry Classification (ITEM6010 in Worldscope database). There are 11 industries in our first industry set and 6 industries in the second industry set. The details of the industry classifications are provided in Appendix II.

4.2 Variable Construction and Research Design

In this thesis, the first study investigates the relationship between dark trading (block trading) and firm valuation and the second one tests the relationship between dark trading (block trading) and default risk. The sample sizes are different in the two studies. There are 3,687 firm-year observations including 708 stocks in the sample for the first, and 6,049 firm-year observations comprising 918 firms in the sample for the second. There are two reasons for fewer observations and stocks in our first study compared to the sample in the second study. Firstly, our first study includes nine control variables in the baseline regressions, while the second study includes five control variables. More observations are deleted in the first study due to missing variables compared to the second study. Secondly, in the first study analyst coverage is included as a control variable. The data of analyst coverage contains many missing values which contribute to a smaller sample than the second study.[58] In what follows, Sections 4.2.1, 4.2.2, and 4.2.3 discuss variable construction, summary statistics, and research design of the first study, and Sections 4.2.4, 4.2.5, and 4.2.6 discuss those of the second study.

4.2.1 Variable Construction for the Study of Firm Valuation

The first study of the thesis investigates the impacts of dark and block trading on firm value which is measured by Tobin's Q (*Q*). The dependent variable *Q* is defined as market

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[58] Our findings in the first study remain robust when analyst coverage is excluded as a control variable.

value of assets divided by book value of total assets, where the market value of assets equals to market value of equity plus book value of assets subtract book value of equity and balance sheet deferred taxes.[59] Our calculation of Tobin's Q is widely used in the literature as a proxy of firm valuation (e.g., Morck, Shleifer, and Vishny, 1988; Yermack, 1996; La Porta, Lopez-de-Silanes, Shleifer, and Vishny, 2002; Gompers, Ishii, and Metrick, 2003; Fang, Noe, and Tice, 2009).

We include nine control variables in the baseline regressions following existing literature about firm valuation (e.g., La Porta, Lopez-de-Silanes, Shleifer, and Vishny, 2002; Spiegel and Wang, 2005; Henry, 2008; Fang, Noe, and Tice, 2009; Roll, Schwartz, and Subrahmanyam, 2009; Ammann, Oesch and Schmid, 2011). For instance, following Roll, Schwartz, and Subrahmanyam (2009) we control for the natural logarithm of market capitalization (*SIZE*) as a proxy of size variation on firm characteristics, the annual share turnover in the stock (*TURNOVER*) as a proxy of the effects of stock trading activity on firm performance, long-term debt of the firm (*LTD*) measured by long-term debt over total assets as a proxy of capital structure, capital expenditures of the firm (*CAPX*) measured as capital expenditures over total assets as a proxy of investment opportunities, a dummy variable which equals one if a firm pays dividend and zero otherwise (*DIVD*) indicating a proxy of capital constraints and investment opportunities, and the return on assets (*ROA*) measured by net income over total assets as a proxy of firm profitability.

[59] Tobin's Q ratio (*Q*) = Market value of assets / Book value of total assets = (Market value of equity + Book value of assets - Book value of equity – Balance sheet deferred taxes) / Book value of total assets.

These control variables are shown to have relationship with firm valuation in the literature. For instance, larger firms are expected to have greater efficiency and valuation as firm size is an outcome of discovery and exploitation of a superior technology in the firm (Peltzman, 1977). Long-term debt reflects the distress of the firm and expects to reduce firm valuation. Capital expenditures capture the investment opportunities undertaken. More firm investment introduces higher growth opportunities and results in a higher Tobin's Q ratio. Non-dividend paying firms may also be viewed as growth-orientated firms, and therefore they tend to have higher valuation compared to dividend paying firms. A relationship between ROA and firm valuation exists in two contrasting aspects. On one hand, higher ROA reflects that profitable firms may have favorable investment opportunities that lead to higher valuation. On the other hand, high ROA may signal mature firms. Compared with immature firms with high developing potential, these firms have limited growth opportunities which leads to a low valuation. Following Amihud and Mendelson (1986) and Roll, Schwartz, and Subrahmanyam (2009), we include share turnover in the regressions to control for the effects of stock trading activities on firm valuation.

In addition, Roulstone (2003) argues that analyst coverage could affect stock market liquidity. Fang, Noe, and Tice (2009) also include analyst coverage as an explanatory variable in the firm performance analysis. Follow the literature, we include analyst coverage in the stock (*ANALYST*) as a control variable which is measured as natural logarithm of one plus the number of analysts who issue at least one earnings forecast for the firm in the I/B/E/S database during the firm's fiscal year. As argued in Fang, Noe, and Tice (2009), analysts may tend to follow "growth stocks" more than "value stocks" and their following can create attention to the firm, which are both likely to increase firm valuation.

Several papers indicate that institutional investor ownership is related to firm performance (see, e.g., McConnell and Servaes, 1990; Nesbitt, 1994; Agrawal and Knoeber, 1996; Karpoff, Malatesta, and Walkling, 1996; Smith, 1996; Del Guercio and Hawkins, 1999; Duggal and Millar, 1999; Faccio and Lasfer, 2000). To control the effect of institutional ownership, we include the institutional ownership of the firm (*IO*) in our baseline regressions. *IO* is measured as the proportion of shares held by institutional investors to total outstanding shares. Institutional investors enhance corporate efficiency in two ways. First, institutional investors perform quality research in order to identify efficient firms for investing funds, and they could direct capital of the firm to its most efficient use. Second, large institutional stakes in public corporations provide strong economic incentives for institutional investors to monitor managers.

Firm idiosyncratic risk (*IDIO*) is also included as a control variable. Spiegel and Wang (2005) demonstrate that idiosyncratic risk is a strong predictor of returns. Fang, Noe, and Tice (2009) include idiosyncratic risk in their firm performance regressions as an explanatory variable. We use daily stock returns and returns of the All Ordinaries Index over the year to estimate the market model and *IDIO* is measured as the standard deviation of the regression residuals. All the continuous variables are winsorized at the 1st and 99th percentiles to mitigate the influences of outliers in the sample. Details of the variable definitions are also provided in Panel A of Table I.

Insert Table I Here

4.2.2 Summary Statistics for the Study of Firm Valuation

Summary statistics of the first study are represented in Panel B of Table I. The mean and median of Tobin's Q is 1.884 and 1.250, indicating a positively skewed distribution. Dark trading has a mean of 7.5% of total daily dollar trading volume and the average of block trading ratio is 4.0%. It indicates that a significant amount of trading activities in the Australian equity markets are contributed by trades without pre-trade transparency. The mean of the natural logarithm of dark trading ratio (*DARK*) is -3.152, and that of block trading ratio (*BLOCK*) is -4.468.

The average market capitalization in our sample is A$1.359 billion (average natural logarithm of market capitalization is 19.431). The sample averages of our turnover variable (*TURNOVER*) and capital expenditure variable (*CAPX*) are 0.008 and 0.095, respectively. The institutional ownership variable (*IO*) has a mean of 0.081. The average of our analyst coverage variable (*ANALYST*) is 1.306 and the corresponding number of analysts following is 2.691. The mean of our idiosyncratic risk (*IDIO*) is 0.031.

The mean and median of long-term debt (*LTD*) in our sample are 0.156 and 0.088, respectively. The dividend dummy variable (*DIVD*) has a mean of 0.577 showing that over half of our sample pay dividends in the fiscal year. It is notable that the average of ROA is negative which is -8.1%. Following Roll, Schwartz, and Subrahmanyam's (2009) explanation, the negative average ROA is probably caused by the bad performance of small firms during the sample period. The average annual share turnover (0.8%) in our sample is smaller than the one reported in the U.S. analysis (see, e.g., Roll, Schwartz, and Subrahmanyam 2009), however, it is similar to Kraft, Schartz, and Weiss (2018).

The correlations between our independent variables are reported in Table II. Dark trading

(*DARK*) is significantly positively correlated with block trading (*BLOCK*). The correlation between *DARK* (*BLOCK*) and *SIZE* is 0.008 (0.227). The significant positive relationship between block trading and firm size indicates that investors are more likely to use block trades to trade stocks of large firms compared to stocks of small firms. As block trades are managed by upstairs brokers and placed for the sale or purchase of a large number of securities, it suggests that investors of larger firms have better access to upstairs brokers and are more likely to meet the minimum trading size requirement of block trading.

Insert Table II Here

There are some high correlations reported in the correlation table. For example, the correlation of *IDIO* and *SIZE* is -0.618, that of *ANALYST* and *SIZE is 0.704*, and that of *IDIO* and *DIVD* is -0.646, and these figures are comparably high. To ensure that our analysis is not subject to multicollinearity, we calculate the variance inflation factor (VIF) for all independent variables in Panel A of Appendix III; they are all lower than 2.7, well below the multicollinearity threshold.[60]

4.2.3 Baseline Specification for the Study of Firm Valuation

To test whether dark trading activities and block trading activities improve, harm, or have no impact on firm valuation, we regress Tobin's Q on dark trading or/and block trading and control variables. We lag all independent variables by one year to reduce the issue of reverse causality. Industry fixed effects are included in our regression to control for time-invariant unobservable industry characteristics, and year fixed effects are included to control for

[60] A VIF of 5 or 10 and above indicates a multicollinearity problem. In some studies, for example O'Brien (2007), the lowest threshold is suggested to be as low as 4.

economy-wide shocks. In the baseline specification, industry fixed effects are constructed based on 2-digit GICS code, called as Industry1. To check the robustness of the study, we include alternative industry classifications based on General Industry Classification code, called as Industry2. The baseline specification is defined as Equation (1) and Equation (2) below:

$$Q_{i,t} = \alpha + \beta_1 DARK_{i,t-1} + \gamma_1 SIZE_{i,t-1} + \gamma_2 TURNOVER_{i,t-1} + \gamma_3 IO_{i,t-1} + \gamma_4 ANALYST_{i,t-1} + \gamma_5 LTD_{i,t-1} + \gamma_6 CAPX_{i,t-1} + \gamma_7 IDIO_{i,t-1} + \gamma_8 DIVD_{i,t-1} + \gamma_9 ROA_{i,t-1} + INDUSTRY_i + YEAR_{t-1} + \varepsilon, \quad (1)$$

$$Q_{i,t} = \alpha + \beta_1 BLOCK_{i,t-1} + \gamma_1 SIZE_{i,t-1} + \gamma_2 TURNOVER_{i,t-1} + \gamma_3 IO_{i,t-1} + \gamma_4 ANALYST_{i,t-1} + \gamma_5 LTD_{i,t-1} + \gamma_6 CAPX_{i,t-1} + \gamma_7 IDIO_{i,t-1} + \gamma_8 DIVD_{i,t-1} + \gamma_9 ROA_{i,t-1} + INDUSTRY_i + YEAR_{t-1} + \varepsilon, \quad (2)$$

where $Q_{i,t}$ is Tobin's Q of firm *i* at the end fiscal year *t*. The natural logarithm of dark trading ratio ($DARK_{i,t-1}$) is our independent variable and measured for firm *i* in year *t-1*, as well as the natural logarithm of block trading ratio ($BLOCK_{i,t-1}$). The control variables are the natural logarithm of market capitalization (*SIZE*), the annual share turnover in the stock (*TURNOVER*), institutional ownership of the firm (*IO*), analyst coverage in the stock (*ANALYST*), long-term debt of the firm (*LTD*), capital expenditures of the firm (*CAPX*), idiosyncratic risk of the stock (*IDIO*), a dummy variable indicating whether the firm pays a dividend (*DIVD*), and the return of assets (*ROA*), which are all measured for firm *i* in year *t-1*. *INDUSTRY* stands for industry fixed effect and *YEAR* stands for year fixed effect. The regression coefficient of *DARK* (*BLOCK*) captures the impact of dark (block) trading on firm valuation.

To examine the effects of dark trading and block trading activities on firm valuation, we also regress Tobin's Q on dark trading and block trading together with all control variables and all independent variables are lagged by one year in this model. This baseline specification is defined as Equation (3) below:

$$Q_{i,t} = \alpha + \beta_1 DARK_{i,t-1} + \beta_2 BLOCK_{i,t-1} + \gamma_1 SIZE_{i,t-1} + \gamma_2 TURNOVER_{i,t-1} + \gamma_3 IO_{i,t-1} + \gamma_4 ANALYST_{i,t-1} + \gamma_5 LTD_{i,t-1} + \gamma_6 CAPX_{i,t-1} + \gamma_7 IDIO_{i,t-1} + \gamma_8 DIVD_{i,t-1} + \gamma_9 ROA_{i,t-1} + INDUSTRY_i + YEAR_{t-1} + \varepsilon. \tag{3}$$

4.2.4 Variable Construction for the Study of Default Risk

We first construct the measure of default risk. Merton (1974) proposes the concept of distance-to-default (*DD*) measure. As an extension from Modigliani and Miller (1958) (known as the Modigliani-Miller theorem), Merton (1974) models firm value including the price of corporate liabilities.[61] A firm default when its asset value falls below the face value of the firm's debt. The model calculates a distance-to-default (*DD*) measure (known as the Merton distance to default model or the Merton *DD* model) and then substitutes it into a cumulative standard normal distribution to compute the probability that the value of a firm's assets will be less than the face value of its debt. The Merton (1974) model has been widely used in studies conducted on default risk (see, e.g., Kealhofer and Kurbat, 2001; Crosbie and Bohn, 2003; Vassalou and Xing, 2004; Duffie, Saita, and Wang, 2007).

However, Bharath and Shumway (2008) argue that the Merton DD model does not produce a sufficient statistic for the probability of default because the model's predictive power mainly comes from its functional form, not the actual default probability produced by the

[61] The Merton (1974) model considers the equity of a firm to be a call option on the underlying value of the firm with a strike price equal to the face value of the firm's debt.

model. Campbell, Hilscher, and Szilagyi (2008) also come to a similar conclusion. Bharath and Shumway (2008) further propose a "naïve" default probability measure simplifying the calculation in Merton model. The measure in the "naïve" model retains the Merton model's structural form and basic inputs. In the empirical tests of the accuracy of "naïve" default probability in Bharath and Shumway (2008), the authors show their "naïve" measure performs better than the original Merton DD model.[62] A recent empirical study on default risk (Brogaard, Li, and Xia, 2017) adopts the "naïve" default probability as the proxy of default risk instead.

Following Bharath and Shumway (2008) and Brogaard, Li, and Xia (2017), we calculate expected default frequency (*EDF*), the naïve predictor, as the measure of default risk in our study. For robustness, we include one-year expected default frequency (*EDF_1y*) and five-year expected default frequency (*EDF_5y)* as the dependent variable, respectively.[63] Specifically, we first calculate the approximation of the volatility of firm asset ($\sigma_{Vi,t}$) for stock *i* in year *t* following the equation below:

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[62] To test the performance of the Merton's DD model and the naïve model, Bharath and Shumway (2008) examine the measures in hazard models (specifically, Cox proportional hazard model, details estimating the proportional hazard model can be found in Cox and Oakes, 1984) and in out-of-sample forecasts. Many studies use hazard models to test the accuracy of the bankruptcy prediction. Shumway (2001) and Chava and Jarrow (2004) argue that hazard models are superior to other types of models. Bharath and Shumway (2008) find the naïve predictor performs better than the Merton DD model in hazard models and in out-of-sample forecasts.

[63] Following prior studies (see, e.g., Brogaard, Li, and Xia, 2017), we consider one-year expected default frequency as our main variable of firm default risk. We also extend the predictive horizon to five years and consider the five-year expected default frequency as our alternative measure of firm default risk to examine the robustness of our findings. More importantly, considering five-year expected default frequency enables us to examine the long-run impact of dark trs negates ding activities on firm default risk.

$$\sigma_{Vi,t} = \frac{EQUITY_{i,t}}{EQUITY_{i,t} + DEBT_{i,t}} \times \sigma_{Ei,t} + \frac{DEBT_{i,t}}{EQUITY_{i,t} + DEBT_{i,t}} \times (0.05 + 0.25 \times \sigma_{Ei,t}), \tag{4}$$

where $EQUITY_{i,t}$ is the market value of equity at the end of fiscal year, $DEBT_{i,t}$ is the face value of debt at the end of fiscal year, and $\sigma_{Ei,t}$ is the annualized stock return volatility calculated based on daily returns in year *t*.

After getting $\sigma_{Vi,t}$, we then calculate distance-to-default ($DD_{i,t}$) using the following equation:

$$DD_{i,t} = \frac{log\left(\frac{EQUITY_{i,t} + DEBT_{i,t}}{DEBT_{i,t}}\right) + \left(r_{i,t-1} - 0.5 \times \sigma^2_{Vi,t}\right) \times T_{i,t}}{\sigma_{Vi,t} \times \sqrt{T_{i,t}}}, \tag{5}$$

where $DD_{i,t}$ is the distance-to-default for stock *i* in year *t*, $\sigma_{Vi,t}$ is the approximation of the volatility of firm asset calculated from Equation (4), $r_{i,t-1}$ is the one-year lagged annual return for stock *i*, and $T_{i,t}$ represents the forecast horizon and is set to one for calculating one-year distance-to-default and five for five-year distance-to-default. Equation (5) subtracts the face value of the firm's debt from an estimate of the market value of the firm and then divides this difference by an estimate of the volatility of the firm scaled to reflect the horizon of the forecast, leading to a z-score referred to as the distance-to-default. Based on the z-score, a probability measure can be formed by using a cumulative distribution to calculate the corresponding probability.

Finally, the expected default frequency (*EDF*) is calculated as:

$$EDF_{i,t} = N(-DD_{i,t}), \tag{6}$$

where $N(.)$ is the cumulative standard normal distribution function. In particular, Equations (5-

6) specify that the probability of default is the normal cumulative density function of a z-score depending on the firm's underlying value, the firm's volatility, and the face value of the firm's debt. A higher distance-to-default is associated with a lower expected default frequency (i.e., a lower probability of default). If the forecast horizon $T_{i,t}$ is set to one (five) in Equation (5), the expected default frequency in Equation (6) measures the probability of default over the one-year (five-year) horizon.

The control variables in the study are included following Bharath and Shumway (2008) and Brogaard, Li, and Xia (2017). *Ln(Equity)* is the natural logarithm of market value of equity. *Ln(Debt)* is the natural logarithm of debt value. $1/\sigma_E$ is the inverse of the annualized stock return volatility calculated based on daily returns. Excess return (*EX_RET*) is the difference between the stock's annual return and the All Ordinaries index annual return. *ROA* is the ratio of net income to total asset. Definitions of the variables are also provided in Panel A of Table III. We winsorize all the variables at the 1st and 99th percentiles to mitigate the influences of outliers in the sample.

Insert Table III Here

4.2.5 Summary Statistics for the Study of Default Risk

Summary statistics are represented in Table III Panel B. An average firm in the sample has a one-year expected default frequency (*EDF_1y*) of 8.50%. Similar to the study of Bharath and Shumway (2008) and Brogaard, Li, and Xia (2017), the default rate in our sample is also highly skewed to the right. We also include five-year expected default frequency as an alternative dependent variable. The average five-year expected default frequency (*EDF_5y*) is 24.8% and is also highly skewed to the right. Dark trading has a mean of 8.8% of total trading volume and the average of block trading of total trading volume is 3.4%.[64]

The control variables are relatively standard and have reasonable variations. For example, the average of market value of equity (*EQUITY*) is A$1.454 billion. The average value of debt is equal to A$0.691 billion. The average return volatility of the stocks (σ_E) is 64.0% and the mean of excess return (*EX_RET*) is 1.315. In line with our first study of firm valuation, we have a negative average *ROA* equal to -0.070 in this study.

The correlations between our independent variables are reported in Table IV. Dark trading is positively correlated with market value of equity, as well as block trading. Block trading is significantly correlated with debt value, while the correlation between dark trading and debt value is insignificant. The inverse of the annualized stock return volatility is negatively correlated with dark trading and block trading. Dark trading is positively correlated with excess return while the correlation of block trading is insignificant. ROA is significantly related to dark trading but its relationship to block trading is insignificant. To ensure that our analysis is not subject to multicollinearity, we calculate the variance inflation factor (VIF) for all independent variables in Panel B of Appendix III and they are all lower than 2.4, well below the multicollinearity threshold of 4.

Insert Table IV Here

4.2.6 Baseline Specification for the Study of Default Risk

To test whether dark trading activities and block trading activities do impact on firm default risk, we regress the one-year or five-year expected default frequency (*EDF_1y* or

[64] The sample of dark and block trades is similar to the variables in the study of firm valuation. For comparison, in the analysis of firm valuation the mean of *DARK* is 7.5% and the mean of *BLOCK* is 4.0%.

EDF_5y) on dark trading (*DARK*) or/and block trading (*BLOCK*) as well as control variables. We lag all independent variables by one year to reduce the issue of reverse causality. Industry and year fixed effects are included in our regressions. We use 2-digit GICS code as the industry fixed effects in baseline specification, and adopt alternative industry classifications based on General Industry Classification code in robustness checks. The baseline specification is defined as Equation (7) and Equation (8) below:

$$EDF\_1y_{i,t}\ (EDF\_5y_{i,t}) = \alpha + \beta_1 DARK_{i,t-1} + \gamma_1 Ln(EQUITY_{i,t-1}) + \gamma_2 Ln(DEBT_{i,t-1}) + \gamma_3 1/\sigma_{E_{i,t-1}} + \gamma_4 EX\_RET_{i,t-1} + \gamma_5 ROA_{i,t-1} + INDUSTRY_i + YEAR_{t-1} + \varepsilon, \tag{7}$$

$$EDF\_1y_{i,t}\ (EDF\_5y_{i,t}) = \alpha + \beta_1 BLOCK_{i,t-1} + \gamma_1 Ln(EQUITY_{i,t-1}) + \gamma_2 Ln(DEBT_{i,t-1}) + \gamma_3 1/\sigma_{E_{i,t-1}} + \gamma_4 EX\_RET_{i,t-1} + \gamma_5 ROA_{i,t-1} + INDUSTRY_i + YEAR_{t-1} + \varepsilon, \tag{8}$$

where $EDF\_1y_{i,t}$ $(EDF\_5y_{i,t})$ is the one-year (five-year) expected default frequency for firm *i* in year *t*, and $DARK_{i,t-1}$ ($BLOCK_{i,t-1}$) is the natural logarithm of dark (block) trading ratio measured for firm *i* in year *t-1*. The control variables are all lagged by one-year. *Ln(Equity)* is the natural logarithm of market value of equity. *Ln(Debt)* is the natural logarithm of debt value. $1/\sigma_E$ is the inverse of the annualized stock return volatility. Excess return (*EX_RET*) is the difference between the stock's annual return and the All Ordinaries index annual return. *ROA* is the ratio of net income to total asset. *INDUSTRY* represents the 2- digit GICS code industry fixed effect and *YEAR* stands for year fixed effect. The regression coefficient of *DARK* (*BLOCK*) captures the impact of dark (block) trading on firm default risk.

To examine the effects of dark trading and block trading activities on firm default risk, we also regress expected default frequency on dark trading and block trading together with all control variables and all independent variables are lagged by one year in this model. This baseline specification is defined as Equation (9) below:

$$EDF\_1y_{i,t}\ (EDF\_5y_{i,t}) = \alpha + \beta_1 DARK_{i,t-1} + \beta_2 BLOCK_{i,t-1} + \gamma_1 Ln(EQUITY_{i,t-1}) + \gamma_2 Ln(DEBT_{i,t-1}) + \gamma_3 1/\sigma_{E_{i,t-1}} + \gamma_4 EX\_RET_{i,t-1} + \gamma_5 ROA_{i,t-1} + INDUSTRY_i + YEAR_{t-1} + \varepsilon. \tag{9}$$

Chapter 5

Empirical Results for the Study of Firm Valuation

5.1 Empirical Results of Baseline Regressions

In the baseline specification, we first estimate Equation (1) by using pooled ordinary least squares (OLS) regression of firm value as measured by Tobin's Q (*Q*) and report the regression estimates in Panel A of Table V. Column 1 considers the specification without fixed effects and the coefficient of dark trading measure (*DARK*) is significantly negative at the 1% level. It supports the first hypothesis (H1) that dark trading activities harm firm value. In particular, a one-standard-deviation increase in *DARK* decreases *Q* by 14.88% of its mean, which indicates that the effect of dark trading is also economically substantial.[65]

Insert Table V Here

Columns 2 and 3 include industry fixed effects and both industry and year fixed effects with industry fixed effects constructed based on 2-digit GICS code (*Industry1*), and the coefficient of *DARK* remains significantly negative at the 1% level. Using the results in Column 3 as an example, we find that a one-standard-deviation increase in *DARK* leads to a decrease of 0.326 in firm value (*Q*) which equals to 17.3% of its mean.[66] Alternatively, we classify industry based on General Industry Classification (*Industry2*) and report the regression results with industry fixed effects and both industry and year fixed effects in Columns 4 and 5. The negative relationship between *DARK* and *Q* continues to hold.

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[65] Because the sample standard deviation of *DARK* is 1.575 and the regression coefficient of *DARK* is -0.178, we have -0.178×1.575=-0.28035. Given that the sample mean of *Q* is 1.884 as shown in Panel B of Table I, we have -0.28035/1.884=-0.1488.

[66] Because the sample standard deviation of *DARK* is 1.575 and the regression coefficient of *DARK* is -0.207, we have -0.207×1.575=-0.326. Given that the sample mean of *Q* is 1.884 as shown in Panel B of Table I, we have -0.326/1.884=-0.173.

To examine the impact of block trading activities on firm value, we estimate Equation (2) by using OLS regression and report the regression estimates in Panel B of Table V. Although the coefficient of block trading measure (*BLOCK*) is significant in Column 1 without fixed effects and Columns 2 and 4 with industry fixed effects, the coefficient becomes insignificant when both industry and year fixed effects are included as shown in Columns 3 and 5. It shows that the impact of block trading activities on firm value is not robust and subsumed by economic-wide factors.

We further estimate Equation (3) by examining the effects of both dark trading activities and block trading activities on firm value and the regression results are reported in Panel C of Table V. The relationship between *DARK* and *Q* is significantly negative in all specifications considered, while the coefficient of *BLOCK* is always insignificant. It confirms that dark trading activities have a detrimental effect on firm value, which is consistent with our first hypothesis (H1). The effect of *DARK* is economically significant even after controlling for block trading activities and control variables. As shown in Panel C, the regression coefficient of *DARK* ranges from -0.138 to -0.209. As the sample standard deviation of *DARK* is 1.575, a one-standard-deviation increase in *DARK* corresponds to a reduction of 0.217 to 0.329 in *Q* which equals to 11.54% to 17.47% of its mean. The emergence of dark pools enables trading with less pre-trade transparency and stimulates dark trading activities. Our results reveal that firm performance is adversely affected by dark trading activities. Prior studies document the impacts of dark trading on several aspects of market quality although their evidence is mixed (see, e.g., Ray, 2010; Comerton-Forde and Putninš, 2015; Foley and Putninš, 2016). Our analysis directly examines whether the impacts of dark trading are translated to variations in firm performance.

Block trading activities are managed by upstairs brokers with limited pre-trade transparency and executed outside the dark pools. In Panel C of Table V, we find an insignificant effect of *BLOCK* on firm value in all specifications considered. Given that the coefficient of *BLOCK* is significant at the 1% level in Columns 1, 2 and 4 of Panel B, our results in Panel C indicate that the effect of block trading activities on firm value is subsumed by the effect of dark trading activities. Taken together, we do not find evidence of block trading activities affecting firm performance. Since brokers in the upstairs market have a unique role as "information repositories" which allows them to tap into additional liquidity and to signal trading motivation (Grossman, 1992; Bessembinder and Venkataraman, 2004), block trading has lower non-execution risk and more pre-trade transparency compared to dark trading. Our results are consistent with Comerton-Forde and Putninš (2015) which document little impact of block trading on corporate information environment.

Some of our control variables have significant effects on firm value across all regression specifications in Table V. For instance, the regression coefficient of firm size (*Size*) is always positive and significant at the 1% level. It indicates a higher valuation associated with larger firms, which is commonly observed in many studies of firm value (see, e.g., Roll, Schwartz, and Subrahmanyam, 2009). The effect of institutional ownership (*IO*) is significantly negative at the 1% level and it is in line with Morck, Nakamura, and Shivdasani (2000) who focus on Japanese firms. Idiosyncratic risk of the firm (*IDIO*) is significantly and positively related to firm value. It suggests that higher idiosyncratic risk increases market valuation of firm.[67] In line with Roll, Schwartz, and Subrahmanyam (2009), both long-term debt (LTD) and return on assets (ROA) have negative relationships with firm valuation and they are significant at the 1% level.[68]

5.2 Endogeneity and Reverse Causality

Dark trading activities and block trading activities are potentially endogenous as traders likely take into account firm valuation when choosing the trading venues. In addition, some unobserved factors can simultaneously affect trading activities and firm valuation. To mitigate the concern of reverse causality, we adopt lagged independent and control variables in our baseline specifications. We also include a set of control variables and industry and year fixed effects to alleviate the endogeneity issue caused by the omitted variable bias. To further address concerns of endogeneity and reverse causality, we adopt four types of additional tests in this section including: (i) controls of firm fixed effects; (ii) two-stage least squares (2SLS) regressions; (iii) testing changes around an exogenous shock in dark trading; and (iv) difference-in-differences tests. These tests are constructed following studies related to dark trading or firm valuation or firm performance (see, e.g., Fang, Noe, and Tice, 2009; Fang, Tian,

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[67] Some studies show that idiosyncratic risk is positively related to corporate growth options (e.g., Cao, Simin, and Zhao, 2008). Moreover, Kraft, Schartz, and Weiss (2018) demonstrate that Tobin's Q increases with more growth options. Our results remain qualitatively similar without controlling for idiosyncratic risk.

[68] Roll, Schwartz, and Subrahmanyam (2009) explain the negative relationship between firm value and ROA as stocks with high current income are in the "mature" phase of their lifecycle with fewer opportunities for future growth.

and Tice, 2014; Comerton-Forde and Putninš, 2015).[69]

5.2.1 Firm Fixed Effects

There may exist unobservable variables that are correlated with both dark/block trading activities and firm performance and make coefficient estimates in the baseline specifications biased. For example, companies managed by poor quality managers are likely to experience more dark trading activities, and tend to have lower firm valuation. In this case, manager quality is unobservable and correlated with both dark trading activities and firm valuation. Consequently, more dark trading activities could be related to lower firm valuation, however, it is not due to dark trading activities.

As argued in Fang, Noe, and Tice (2009), firm fixed effects can be used as an endogeneity control if the unobservable variables correlated with dark/block trading activities and industry-adjusted performance are constant over time. We replace industry fixed effects with firm fixed effects in the baseline specifications (i.e., Equations (1-3)) and adjust all variables except for dummy variables (i.e., *DIVD* in Equations (1-3)) by subtracting the median of the firm's industry classified based on 2-digit GICS codes.[70] Following Fang, Noe, and Tice (2009), we regress industry-adjusted firm value on industry-adjusted measures of dark trading and block

[69] Specifically, Fang, Noe and Tice (2009) consider 2SLS regressions, controls of firm fixed effects, changes around an exogenous shock to address the concern of endogeneity and reverse causality. Fang, Tian and Tice (2014) adopt a difference-in-differences approach that relies on the exogenous variation in liquidity generated by regulatory changes. Comerton-Forde and Putninš (2015) consider 2SLS regressions to address the potential endogeneity of dark trading. Following these studies, we consider 2SLS regressions, firm fixed effects, changes around an exogenous shock, and difference-in-differences test in this study.

[70] Among the variables in Equations (1-3), *DIVD* is a dummy variable indicating whether the firm pays a dividend and it is not adjusted.

trading, unadjusted measures of dummy control variables, industry-adjusted measures of non-dummy control variables, and firm and year fixed effects as specified below:

$$Adjusted\_Q_{i,t} = \alpha + \beta_1 Adjusted\_DARK_{i,t-1} + \beta_2 Adjusted\_BLOCK_{i,t-1} + \gamma_1 Adjusted\_SIZE_{i,t-1} + \gamma_2 Adjusted\_TURNOVER_{i,t-1} + \gamma_3 Adjusted\_IO_{i,t-1} + \gamma_4 Adjusted\_ANALYST_{i,t-1} + \gamma_5 Adjusted\_LTD_{i,t-1} + \gamma_6 Adjusted\_CAPX_{i,t-1} + \gamma_7 Adjusted\_IDIO_{i,t-1} + \gamma_8 DIVD_{i,t-1} + \gamma_9 Adjusted\_ROA_{i,t-1} + FIRM_i + YEAR_{t-1} + \varepsilon \quad (10)$$

where $Adjusted\_Q_{i,t}$ is the industry-adjusted Tobin's Q at the end of firm *i*'s fiscal year *t*. $Adjusted\_DARK_{i,t-1}$ is industry-adjusted dark trading variable of firm *i* in year *t-1* and $Adjusted\_BLOCK_{i,t-1}$ is industry-adjusted block trading variable of firm *i* in year *t-1*. Similarly, all the control variables are industry-adjusted except for *DIVD*. The control variables are calculated for firm *i* in year *t-1* and include industry-adjusted natural logarithm of the firm's market capitalization (*Adjusted_SIZE*), industry-adjusted annual share turnover in the stock (*Adjusted_TURNOVER*), industry-adjusted institutional ownership of the firm (*Adjusted_IO*), industry-adjusted analyst coverage of the firm (*Adjusted_ANALYST*), industry-adjusted long-term debt of the firm (*Adjusted_LTD*), industry-adjusted capital expenditures of the firm (*Adjusted_CAPX*), industry-adjusted idiosyncratic risk of the firm (*Adjusted_IDIO*), a dummy variable indicating whether the firm pays a dividend (*DIVD*), and industry-adjusted return of assets of the firm (*Adjusted_ROA*). $FIRM_i$ stands for firm fixed effect and $YEAR_{t-1}$ stands for year fixed effect.[71]

The regression results of using industry-adjusted variables and firm fixed effects are reported in Columns 1 to 3 of Table VI. The effect of *Adjusted_DARK* on *Adjusted_Q* is significantly negative at the 1% level, while the effect of *Adjusted_BLOCK* becomes insignificant in Column 3 when both dark and block trading activities are taken into consideration. Estimates show that an increase in industry-adjusted measure of dark trading activities leads to a decrease in the industry-adjusted Q ratio. The impact of industry-adjusted measure of block trading activities (*Adjusted_BLOCK*) is largely subsumed by the impact of industry adjusted measure of dark trading activities (*Adjusted_DARK*), as evidenced by the little relationship between *Adjusted_BLOCK* and *Adjusted_Q*. In Columns 4 to 6 where year fixed effects are further included to control for economy-wide shocks, *Adjusted_DARK* continues to wield a significant negative effect on *Adjusted_Q* while the coefficient of *Adjusted_BLOCK* remains insignificant in Column 6. It confirms that our findings of the adverse effect of dark trading activities on firm value and the little relationship between block trading activities and firm value in the baseline specifications are robust to the inclusion of firm fixed effects.

Insert Table VI Here

Also, the results of control variables are largely consistent with their results in the baseline specifications except for institutional ownership (*IO*). Let us take Column 3 or 6 as an example,

[71] "TICKER SYMBOL" collected from Thomson Reuters Worldscope database is adopted as our firm identifier. According to the Thomson Reuters Data Definitions Guide 2013 (ISSUE 14.2), "*TICKER SYMBOL represents a symbol used to identify the company on the stock exchanges where it is listed.*"

industry adjusted measures of firm size (*SIZE*), long-term debt (LTD), idiosyncratic risk (*IDIO*), and return on assets (*ROA*) continue to have a similar effect on industry-adjusted Q ratio. However, the effect of industry-adjusted institutional ownership (*Adjusted_IO*) is significant in Column 3, yet nonetheless becomes insignificant in Column 6 when year fixed effects are further controlled for. It suggests there are economic-wide variables driving the relationship between institutional ownership and firm valuation, and therefore such a relationship disappears after controlling for year fixed effects.

5.2.2 Two-Stage Least Squares (2SLS) Regressions

In this section, we use 2SLS instrumental variable regressions to control for endogeneity, which do not require the unobservable variables to be constant across time as in the approach of including industry or firm fixed effects. The approach of instrumental variable is widely used in the literature to estimate causal relationships when controlled experiments are not feasible or when a treatment is not successfully delivered to every unit in a randomized experiment (Imbens and Angrist, 1994). A valid instrument induces changes in the explanatory variables but has no independent effect on the dependent variable so that the causal effect of the explanatory variable on the dependent variable can be uncovered. 2SLS regressions serve as a computational method for calculating estimates of instrumental variables.

To explicitly address the potential endogeneity of dark trading activities, we adopt an instrumental variable approach by constructing a set of two instruments based on market structure changes that are exogenous with respect to firm value but influence the amount of dark trading. Following Comerton-Forde and Putninš (2015), we consider the removal of the ten-second rule on 30 November 2009 as the first market structure change. The ten-second rule requires the ASX broker to place an order in the CLOB for ten seconds before executing dark trades, and its removal makes execution of dark trades easier.[72] In other words, dark trading activities are expected to increase after the removal of the ten-second rule. To capture this exogenous change, we construct a dummy variable $D^{rule\ remove}$ which equals to 1 if the fiscal year ending date of the firm occurs after the removal of the ten-second rule on 30 November 2009 and 0 otherwise, and adopt it as an instrumental variable to dark trading activities.

The second market structure change refers to the change in ASX trading fees on 1 July 2010 which occurs largely in anticipation of competition from other market operators and changes the relative explicit costs of trading in the dark compared to trading in the CLOB.[73] Several days earlier in June 2010, the ASX launched its first exchange-based dark pool called Centre Point, which has an impact on dark trading activities and is unlikely to be related to performance of Australian firms. As the change in trading fee and the launch of Centre Point take place several days apart, we consider them as two concurrent events in our analysis of firm-year observations. Following Comerton-Forde and Putninš (2015), we construct a single

[72] The 10-second rule requires brokers to show their trading in the CLOB for ten seconds and the size of the displayed order is one share. Although it seems difficult for other investors to access the order with only one share offered, the 10-second rule provides information to the public, especially to the high frequency traders, and increases pre-trade transparency. Removing the rule on 30 November 2009 offers convenience and intergraded pre-trade information protection to dark traders.

[73] Details on the changes in ASX Fees and Activity Rebate can be found from the ASX market announcement: https://www.asx.com.au/documents/investor-relations/20100603_asx_fees_and_rebates.pdf. Starting from 1 July 2010, on-market crossing and off-market crossing execution fees are reduced from 0.15 basis points (bps) to 0.10 bps, and from 0.075 bps to 0.05 bps, respectively. The trade execution fee for trades occurring during the auction process remains at 0.28 bps. The headline trade execution fee is reduced from 0.28 bps to 0.15 bps.

dummy variable $D^{fee\ reduce}$ as another instrument variable to dark trading activities, which equals 1 if the fiscal year ending date of the firm occurs after both events occur (i.e., after 1 July 2010) and 0 otherwise.

In the first-stage regressions of our 2SLS instrumental variable approach, measures of dark trading and block trading are regressed on the set of two instrumental variables, control variables and industry fixed effects, respectively, as specified in Equations (11) and (12) below:

$$DARK_{i,t} = \alpha + \beta_1 D_{i,t}^{rule\ remove} + \beta_2 D_{i,t}^{fee\ reduce} + \gamma_1 SIZE_{i,t} + \gamma_2 TURNOVER_{i,t} + \gamma_3 IO_{i,t} + \gamma_4 ANALYST_{i,t} + \gamma_5 LTD_{i,t} + \gamma_6 CAPX_{i,t} + \gamma_7 IDIO_{i,t} + \gamma_8 DIVD_{i,t} + \gamma_9 ROA_{i,t} + INDUSTRY_i + \varepsilon \tag{11}$$

$$BLOCK_{i,t} = \alpha + \beta_1 D_{i,t}^{rule\ remove} + \beta_2 D_{i,t}^{fee\ reduce} + \gamma_1 SIZE_{i,t} + \gamma_2 TURNOVER_{i,t} + \gamma_3 IO_{i,t} + \gamma_4 ANALYST_{i,t} + \gamma_5 LTD_{i,t} + \gamma_6 CAPX_{i,t} + \gamma_7 IDIO_{i,t} + \gamma_8 DIVD_{i,t} + \gamma_9 ROA_{i,t} + INDUSTRY_i + \varepsilon \tag{12}$$

where all variables are measured for firm *i* in year *t*, variables of dark trading activities and block trading activities ($DARK_{i,t}$ and $BLOCK_{i,t}$) are adopted as the dependent variables, $D_{i,t}^{rule\ remove}$ is the dummy variable for the removal of the ten-second rule which equals to 1 if the end date of fiscal year *t* for firm *i* is after the date of rule removal (i.e., 30 November 2009) and 0 otherwise, $D_{i,t}^{fee\ reduce}$ is the dummy variable for the reduction of trading fees which equals to 1 if the end date of fiscal year *t* for firm *i* is after the date of trading fee reduction (i.e., 1 July 2010) and 0 otherwise, and both dummy variables serve as instrumental variables. We adopt the same set of control variables as in the baseline specifications (i.e., as in Equation (1-3)) including natural logarithm of market capitalization (*SIZE*), annual share turnover in the stock (*TURNOVER*), institutional ownership (*IO*), analyst coverage (*ANALYST*), long-term debt (*LTD*), capital expenditures (*CAPX*), idiosyncratic risk (*IDIO*), a dummy variable indicating whether the firm pays a dividend (*DIVD*), and return of assets (*ROA*). *INDUSTRY* stands for industry fixed effect and is constructed based on either 2-digit GICS code (*Industry1*) or General Industry Classification (*Industry2*). The first-stage regressions specified in Equations (11) and (12) are estimated by OLS, respectively, and the fitted value of dark trading activities (*PRE_DARK*) and the fitted value of block trading activities (*PRE_BLOCK*) are adopted as independent variables in the second-stage regressions instead of the observed measures of dark and block trading activities (*DARK* and *BLOCK*). In particular, the second-stage regression of firm valuation as measured by Tobin's Q is specified below:

$$Q_{i,t} = \alpha + \beta_1 PRE\_DARK_{i,t-1} + \beta_2 PRE\_BLOCK_{i,t-1} + \gamma_1 SIZE_{i,t-1} + \gamma_2 TURNOVER_{i,t-1} + \gamma_3 IO_{i,t-1} + \gamma_4 ANALYST_{i,t-1} + \gamma_5 LTD_{i,t-1} + \gamma_6 CAPX_{i,t-1} + \gamma_7 IDIO_{i,t-1} + \gamma_8 DIVD_{i,t-1} + \gamma_9 ROA_{i,t-1} + INDUSTRY_i + \varepsilon \tag{13}$$

where the dependent variable $Q_{i,t}$ denotes Tobin's Q of firm i measured at the end of fiscal year t and all the independent variables and control variables are lagged and measured for firm i in fiscal year $t-1$. *PRE_DARK* is the fitted value from estimating the first-stage regression of dark trading as specified in Equation (11) and *PRE_BLOCK* is the fitted value from estimating the first-stage regression of block trading as specified in Equation (12). Consistent with the baseline specification and the first-stage regression, control variables in the second-stage regressions include: natural logarithm of market capitalization (*SIZE*), annual share turnover (*TURNOVER*), institutional ownership (*IO*), analyst coverage (*ANALYST*), long-term debt (*LTD*), capital expenditures (*CAPX*), idiosyncratic risk (*IDIO*), a dummy variable of dividend payment (*DIVD*), and return of assets (*ROA*). *INDUSTRY* is included to control for industry fixed effects.

Panel A of Table VII reports the results of the first-stage regressions, where the first (second) two columns reports the results of regressing *DARK* and *BLOCK* on instrumental variables and control variables with industry fixed effects constructed based on *Industry1* (*Industry2*). Both instrumental variables are shown to be highly significant related to *DARK* and *BLOCK* and also wield the expected effects. As shown in the first two columns, the regression coefficients of $D^{rule\ remove}$ on *DARK* and *BLOCK* are 3.088 and 2.571 and both are significant at the 1% level. It indicates that the removal of the ten-second rule increases *DARK* by 97.97% of its mean and increases *BLOCK* by 57.54% of its mean.[74] Removing the ten-second rule allows investors to hide order details before execution and makes it more convenient to execute orders without pre-trade transparency. It leads to a dramatic growth in both dark trading activities and block trading activities as expected.

Insert Table VII Here

The second instrument $D^{fee\ reduce}$ captures the event of the ASX reducing trading fees and launching Centre Point − its first exchange-based dark pool. Starting from 1 July 2010, execution fees for on-market crossing (i.e., for dark trades) are reduced from 0.15 bps to 0.10 bps, which lowers transaction costs of dark trading and makes dark trades more attractive to

[74] The regression coefficient of $D^{rule\ remove}$ on *DARK* is 3.088, and the sample mean of *DARK* is -3.152 as shown in Panel B of Table I. When the dummy variable changes from 0 to 1 (i.e., when the ten-second rule is removed), *DARK* is increased by 3.088 which equals to 3.088/3.152=0.9797 of its mean. The sample mean of *BLOCK* is -4.468. and the regression coefficient of $D^{rule\ remove}$ on *BLOCK* is 2.571, which is equal to 2.571/4.468=57.54% of its mean.

investors. The launch of Centre Point creates a trading venue for dark orders and enables execution of dark orders on such an exchange-based dark pool. Both events are expected to stimulate dark trading activities. Block trading activities are managed by upstairs brokers with limited pre-trade transparency and executed outside the dark pools. After June 2010, upstairs brokers can send orders to Centre Point for execution, while investors can directly submit their orders to Centre Point for execution without pre-trade transparency in Centre Point instead of resorting to upstairs brokers for block trading. Therefore, block trading activities are expected to decrease after 1 July 2010 (i.e., when $D^{fee\ reduce}$ equals to 1). As shown in the first two columns in Panel A of Table VII, the regression coefficient of $D^{fee\ reduce}$ on *DARK* is 0.157 and that on *BLOCK* is -0.615. Both of them are significant at the 1% level, and the event of the ASX reducing trading fees and launching Centre Point is shown to increase dark trading activities and decrease block trading activities as expected.[75] In the second two columns of Panel A in Table VII, industry fixed effects are constructed based on General Industry Classification (*Industry2*). The effects of two instrumental variables remain significant and have the expected signs. In addition, the F-statistic ranges from 101.5 to 396.5 in Panel A, strongly indicating that our instruments satisfy the relevance condition. Taken together, the results of the first-stage regressions validate the two dummy variables as valid instrumental variables for dark and block trading activities.

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[75] Since the sample mean of *DARK* (*BLOCK*) is -3.152 (-4.468), it indicates that the event of the ASX reducing trading fees and launching Centre Point increases *DARK* by 0.157/3.152=4.98% of its mean and decreases *BLOCK* by 0.615/4.468=13.76% of its mean.

The results of the second-stage regressions of firm value are reported in Panel B of Table VII. The effect of the fitted value of *DARK* (*PRE_DARK*) is significantly negative in both columns, although its effect in the second column is stronger when industry fixed effects are constructed based on *Industry2*, compared to the first column where *Industry1* is controlled for instead. It consistently supports our first hypothesis that dark trading activities harm firm valuation. The effect of the fitted value of *BLOCK* (*PRE_BLOCK*) is significantly positive at the 5% level in the second column but becomes insignificant in the first column when industry fixed effects are constructed based on 2-digit GICS codes (*Industry1*) instead. Compared to *Industry2* which is constructed based on General Industry Classification and covers 6 industries, the 2-digit GICS codes (*Industry1*) differentiate a wide spectrum of industries and better captures industry heterogeneity in the sample. Our results indicate that the effect of *BLOCK* on firm value disappears after controlling for *Industry1* and is thus not robust, thereby confirming the little impact of block trading activities on firm value.

5.2.3 Changes Around Exogenous Shock

Potential reverse causality is evident in our results, although we have used the lagged independent variables and control variables in regression specifications to partially address this concern. For instance, firms with higher valuation may be sought after by certain groups of institutional investors, and there are more dark trading activities in such stocks because the institutional investors prefer to trade these stocks in dark pools, which results in reverse causality. In this section, we follow Chang, Chen, and Zolotoy (2017) to examine the changes in firm valuation around the exogenous shock of the removal of the ten-second rule to identify the causal effects of dark trading activities on firm valuation. We consider the removal of the ten-second rule as the exogenous shock because it has been demonstrated to have substantial impacts on dark trading activities in Section 5.2.2. As discussed above on the results of the first-stage regressions, the removal of the ten-second rule increases *DARK* by 97.97% of its mean, while the event of ASX reducing trading fees and launching Centre Point increases *DARK* by 4.98% of its mean. Therefore, the removal of the ten-second rule serves as a better candidate as a quasi-natural experiment to dark trades.

Chang, Chen, and Zolotoy (2017) adopt the exogenous shock of decimalization, and examine the changes in crash risk around decimalization using regression analysis. Following them, we rely on firms for which data are available for both the fiscal year before and the fiscal year after the event of the removal of the ten-second rule in 2009 (i.e., for both fiscal years of 2008 and 2010), and construct a post-shock dummy variable (*POST*) that equals to 1 for the fiscal year after the event, and 0 for the fiscal year before the event. The regression model of firm valuation is estimated as follows:

$$Q_{i,t} = \alpha + \beta_1 POST_{i,t} + \beta_2 BLOCK_{i,t-1} + \gamma_1 SIZE_{i,t-1} + \gamma_2 TURNOVER_{i,t-1} + \gamma_3 IO_{i,t-1} + \gamma_4 ANALYST_{i,t-1} + \gamma_5 LTD_{i,t-1} + \gamma_6 CAPX_{i,t-1} + \gamma_7 IDIO_{i,t-1} + \gamma_8 DIVD_{i,t-1} + \gamma_9 ROA_{i,t-1} + INDUSTRY_i + \varepsilon \tag{14}$$

where $Q_{i,t}$ denotes Tobin's Q of firm i in fiscal year t, $POST_{i,t}$ equals 1 if fiscal year t of firm i is after the event of the ten-second rule in 2009 and 0 otherwise, $BLOCK_{i,t-1}$ is the variable of block trading of firm i in fiscal year t, control variables included are lagged and consistent with the baseline specifications (i.e., Equations (1-3)), and $INDUSTRY_i$ denotes industry fixed effects.

Table VIII shows the results of the regression estimated using OLS with industry fixed effects constructed based on either *Industry1* or *Industry2*. In all regression specifications considered, the coefficient for the post-shock dummy is negative and significant at least at the 5% level. Since dark trading activities increase dramatically after the removal of the ten-second rule as shown in Section 5.2.2, the negative coefficient of the post-shock dummy indicates a significant reduction of firm valuation in response to the exogenous shock that increases dark trading. The effect of the exogenous shock is also economically substantial. The coefficient of *POST* ranges from -0.400 to -0.293, which suggests that firm value declines by 0.293 to 0.40 in the after-event year compared to the pre-event year. As we consider firm-year observations of 2008 and 2010 in Equation (14), the number of observations reduces to 612 in the analysis of Table VIII. Even with such a small sample size, the effect of the exogenous shock on firm valuation is highly significant. In line with our previous results, we find a detrimental effect of dark trading activities on firm valuation.

Insert Table VIII Here

5.2.4 Difference-in-Differences Test

In this section we consider the removal of the ten-second rule as a quasi-natural experiment and adopt a difference-in-differences approach to provide more evidence for our findings. Difference-in-differences is a statistical technique used in econometrics and quantitative research in the social sciences that attempts to mimic an experimental research design using observational study data, by studying the differential effect of a treatment on a "treatment group" versus a "control group" in a natural experiment (Bertrand, Duflo, and Mullainathan, 2004). It calculates the effect of a treatment (i.e., an explanatory variable or an independent variable) on an outcome (i.e., a response variable or dependent variable) by comparing the average change over time in the outcome variable for the treatment group, compared to the average change over time for the control group. Difference-in-differences test is widely used in corporate finance literature to address concerns of endogeneity and reverse causality (e.g., Fang, Tian, and Tice, 2014; Brogaard, Li, and Xia, 2017).

In our application of the difference-in-differences approach, we compare the change in the firm valuation for two groups of firms. These two groups have similar characteristics but experience a significantly different change in dark trading activities around the exogenous event. There are several benefits to incorporate the difference-in-differences approach. Firstly, it could address any potential omitted or unobserved variables. Secondly, it only focuses on the year before and after the exogenous event and thus removes biases driven by time trends.

We use "ten-second rule removal" on November 30, 2009 as an exogenous event because dark trading activities are demonstrated to significantly increase after the event while the event is exogenous with respect to firm valuation. As shown in Section 5.2.3, we subtract the sample period to focus on two years: the year before the exogenous event (year 2008) and the year after (year 2010). Following Fang, Tian, and Tice (2014) and Brogaard, Li, and Xia (2017), we first employ a difference-in-differences identification strategy. By using propensity score matching, we form a treatment group and a control group. Specifically, we rank all sample firms based on their changes in *DARK* around the rule removal, and select the top 30% of the firms as treatment group and the bottom 30% of the firms as control group. We then regress a probit model where the dependent variable is a dummy variable that equals to one if the firm is located in the top 30% (treatment group) and 0 if the firm is located in the bottom 30%

(control group). The independent variables in the probit model include measure of dark trading (*DARK*), measure of block trading (*BLOCK*), and all the control variables used in the baseline specification, and all the variables are measured in the year of pre-exogenous shock (year 2008).

Propensity scores serve as predicted probabilities to match firms in the treatment group that experiences the highest increase in *DARK* because of the "10-second rule removal" with firms in the control group that experiences the lowest increase in *DARK* due to the abolition of the rule. Specifically, firms in the top 30% is matched with firms in the bottom 30% by closest propensity score. After the matching procedure, 92 pairs of treatment-control groups are matched. Table IX reports the results of the difference-in-differences test. The results of estimating the probit model are reported in Column 1 of Panel A. The probit model produces a pseudo R^2 of 0.2754 and a chi-square test's p-value less than 0.0001, which suggests that our model specification captures a significant amount of variation in the choice variable.

Insert Table IX Here

Fang, Tian, and Tice (2014) and Brogaard, Li, and Xia (2017) argued that difference-in-differences test relay on the parallel trend assumption.[76] They perform three diagnostic tests to verify whether the assumption holds in their case. Following them, we also conduct three diagnostic tests for the verification of the assumption in our difference-in-differences test. The first diagnostic test is the comparison between before-match probit model and after-match probit model. Specifically, we re-run the probit model for the matched sample. The results are reported in Column 2 of Panel A. Compared with the before-match probit model, the likelihood

[76] Parallel trend assumption assumes that the underlying trends in the outcome variable is the same for both treatment and control groups.

ratio in the after-match model is lower. Meanwhile, the estimates that are significant in the before-match probit model become much smaller and no longer statistically significant in the after-match model. For instance, the regression coefficient of *DARK* is significant at the 1% level in the before-match model and becomes insignificant in the after-match model. Furthermore, the chi-square test's p-value is below 0.0001 for the before-match model but increases to 0.1060 in the after-match model. The same situation happens to the pseudo R^2 which drops dramatically from 0.2754 in the pre-match model to 0.0669 in the after-match model. Our first diagnostic test suggests a weaker relationship between firm characteristic differentials of the treatment and control groups in the matched sample.

The second diagnostic test is examining the difference of propensity scores between treatment group and control group. Panel B of Table IX reports propensity score distribution of treatment group, control group, and differentials of the two groups in the matched sample. The two groups' propensity scores are shown to line up closely. For example, the maximum of the distance between the propensity score of the matched groups is only 0.08. The average of the differential is only 0.013. Our second diagnostic test shows that the propensity score distributions of the matched treatment and control groups are quite similar to each other and their difference is trivial.

The final diagnostic test examines the t-statistics of the differences in the two groups' characteristics before the removal of the ten-second rule (i.e., before the exogenous event). The results are reported in Panel C of Table IX. The t-value of differences between treatment group and control group are largely statistically insignificant.[77] Although the removal of the ten-second rule affects the treatment and control groups differently, the difference in the measure of dark trading activities (*DARK*) between the two groups before the exogenous event is -0.066 and quite small. It means that the two groups have a similar level of dark trading activities before the removal of the ten-second rule. Our third diagnostic tests suggest that the propensity score matching method could restrain the potentially confounding firm differences known to affect firm valuation. Meanwhile, the results are not driven by general time trends. The t-statistics of the differences in the two groups' characteristics after the removal event are reported in Panel D of Table IX. There are significant differences between the treatment and control firms introduced by the "ten-second rule removal". The largest difference is in the dark trading variable (*DARK*) which is 0.583 and statistically significant at the 1% level (t-value=11.392).

Panel E of Table IX shows the difference-in-differences estimator of firm valuation and reports the estimator and corresponding t-value of Tobin's Q (*Q*). Specifically, in the treatment group we calculate the change in firm valuation (*Q*) from pre-event year (2008) to post-event year (2010). Similarly, we calculate the change in *Q* for the control group as well. The gap between the change in *Q* of treatment group and change in *Q* of control group is the estimated difference between the two groups. The gap between treatment group and control group of the change in *Q* is -1.155 and significant at the 1% level, which suggests that firm valuation in the treatment group experiences a significant decrease because of the exogenous shock.

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[77] Although some of the control variables are significant at the 10% level, they are all insignificant at the 5% or 1% level.

Panel F of Table IX reports the results of estimating difference-in-differences regressions based on the specification below:

$$Q_{i,t} = \alpha + \beta_1 TREAT_i \times AFTER_t + \beta_2 TREAT_i + \beta_3 AFTER_t + \gamma_1 BLOCK_{i,t} + \gamma_2 SIZE_{i,t} + \gamma_3 TURNOVER_{i,t} + \gamma_4 IO_{i,t} + \gamma_5 ANALYST_{i,t} + \gamma_6 LTD_{i,t} + \gamma_7 CAPX_{i,t} + \gamma_8 IDIO_{i,t} + \gamma_9 DIVD_{i,t} + \gamma_{10} ROA_{i,t} + INDUSTRY_i + \varepsilon, \tag{15}$$

where *TREAT* is a dummy variable equal to one (zero) if a firm is in the treatment (control) group, *AFTER* is a dummy variable equal to one for 2010 (post-event year) and zero for 2008 (pre-event year), and *TREAT×AFTER* is the interaction between these two variables. The control variables are the same as those used in the probit model in Panel A of Table IX. In addition, we include block trading variable (*BLOCK*) as an explanatory variable in the regression to avoid the omitted variable problem. We also include industry fixed effects to control for unobserved industry characteristics which are constructed based on either 2-digit GICS code (*Industry1*) or General Industry Classification (*Industry2*). As shown in Panel F of Table IX, the interaction term (*TREAT×AFTER*) has a coefficient of -0.924 in Column 1 and -0.945 in Column 2 and both are significant at the 1% level. It indicates a larger drop in the market valuation of the firms in the treatment group following the removal of the ten-second rule compared with firms in the control group. Taken together, our difference-in-differences test is consistent with our baseline finding suggesting that dark trading activities lead to a reduction in firm valuation.

5.3 How Does Dark Trading Harm Firm Valuation?

In this section, we investigate the potential underlying mechanism(s) for dark trading activities to reduce firm valuation. Dark trading is shown to wield impacts on stock liquidity and information efficiency of the exchange market (see, e.g., Degryse, Van Achter, and Wuyts, 2009; Buti, Rindi, and Werner, 2011; Weaver, 2014; Degryse, de Jong and van Kervel, 2015; Kwan, Masulis and McInish, 2015). On the other hand, stock liquidity and information efficiency are documented as influencing firm valuation (see, e.g., Fang, Noe and Tice, 2009; Lang, Lins, and Maffett, 2012). Consequently, we test whether stock liquidity (Hypothesis 1A) and/or information efficiency (Hypothesis 1B) are the underlying mechanisms that link dark trading to firm valuation.

Alternatively, large shareholders' incentives to monitor are likely to be affected by market quality (Maug, 1998; Fang, Noe and Tice, 2009), and therefore dark trading activities could influence the effectiveness of corporate governance. Institutional blockholders refer to institutional investors who own no less than 5% of the shares outstanding and their effectiveness in exerting corporate governance could be related to dark trading ratio which reflects the relative transparency in stock trading activities. Brockman and Yan (2009) show that blockholder ownership increases the profitability of informed trading and idiosyncratic volatility because they have access to private information. Therefore, higher blockholder ownership can be argued to result in higher downside risk and lower firm valuation. Consistent with this argument, Thomsen, Pedersen, and Kvist (2006) find a negative association between blockholder ownership and firm value in Continental Europe. We test corporate governance as the third potential channel through which dark trading undermines firm valuation (Hypothesis 1C).

5.3.1 Stock Liquidity Mechanism

Under the stock liquidity mechanism (Hypothesis 1A), the negative impact of dark trading activities on firm valuation is expected to be stronger for stocks with lower liquidity (i.e., for stocks with higher illiquidity). To test this mechanism, we consider two alternative variables of stock illiquidity: average quoted bid-ask spread (*SPREAD*) and proportion of days with zero returns (*ZERORET*), and both of them are widely used in the literature to proxy for illiquidity (see, e.g., Lesmond, Ogden and Trzcinka,1999; Comerton-Forde and Putninš, 2015; Brogaard, Li, and Xia, 2017). In particular, quoted bid-ask spread is defined as the absolute difference between bid and ask price divided by the mid-point of the best bid and ask price. *SPREAD* is then measured as the average value of quoted spread. Higher *SPREAD* represents higher illiquidity (i.e., lower liquidity). *ZERORET* is defined as number of the days with zero returns divided by number of annual trading days over the fiscal year. A higher *ZERORET* value represents lower liquidity. We lag the illiquidity variable for one year to reduce the concern of reverse causality and allow the effect of *DARK* on firm valuation to vary with the illiquidity variable. Specifically, we consider the interaction regression of firm valuation as below:

$$Q_{i,t} = \alpha + \beta_1 DARK_{i,t-1} + \beta_2 BLOCK_{i,t-1} + \beta_3 SPREAD_{i,t-1}\ (or\ \beta_3 ZERORET_{i,t-1}) + \beta_4 DARK_{i,t-1} \times SPREAD_{i,t-1}\ (or\ \beta_4 DARK_{i,t-1} \times ZERORET_{i,t-1}) + \gamma_1 SIZE_{i,t-1} + \gamma_2 TURNOVER_{i,t-1} + \gamma_3 IO_{i,t-1} + \gamma_4 ANALYST_{i,t-1} + \gamma_5 LTD_{i,t-1} + \gamma_6 CAPX_{i,t-1} + \gamma_7 IDIO_{i,t-1} + \gamma_8 DIVD_{i,t-1} + \gamma_9 ROA_{i,t-1} + INDUSTRY_i + YEAR_{t-1} + \varepsilon, \tag{16}$$

where $Q_{i,t}$ is the dependent variable of firm valuation measured as the Tobin's Q for firm *i* in year *t*, $SPREAD_{i,t-1}$ is measured as the average quoted bid-ask spread measured for firm *i* in year *t-1*, and $ZERORET_{i,t-1}$ is defined as number of the days with zero returns divided by number of annual trading days for firm *i* over year *t-1*. Measure of dark trading $DARK_{i,t-1}$ and that of block trading $\beta_2 BLOCK_{i,t-1}$ are measured for firm *i* in year *t-1*. *DARK×SPREAD* is the interaction term of dark trading and average quoted spread. *DARK×ZERORET* is the interaction term of dark trading and percentage of days with zero return. We consider the same set of control variables as in the baseline specification such as Equation (1) and their definitions are provided in Table I. *INDUSTRY* stands for industry fixed effects constructed based on either 2-digit GICS code (*Industry1*) or General Industry Classification (*Industry2*), and *YEAR* stands for year fixed effects. Under the stock liquidity mechanism (H1A), we expect the interaction term of *DARK* and illiquidity variable to have a negative effect (i.e., $\beta_4 < 0$ in Equation (16)), reflecting a stronger negative effect of *DARK* on firm value for stocks with higher illiquidity.

The regression results of estimating Equation (16) are reported in Panel A of Table X. In Column 1 with *Industry1* included as industry fixed effects and *SPREAD* considered as the illiquidity variable, the estimated coefficients of both *DARK×SPREAD* and *DARK* are significantly negative at the 10% level. It indicates dark trading activities have a negative impact on firm value and this impact becomes more negative for stocks with more quoted bid-ask spread (i.e., with lower liquidity). This finding supports stock liquidity as an underlying mechanism for dark trading to undermine firm value (Hypothesis 1A). When industry fixed effects are constructed based on *Industry2* instead in Column 2, the coefficient of *DARK×SPREAD* is significantly negative at the 5% level, while the coefficient of *DARK* is insignificant. It means that the effect of dark trading activities increases with *SPREAD* (i.e., stock illiquidity), which is also consistent with Hypothesis 1A.

Insert Table X Here

In Columns 3 and 4, *ZERORET* is adopted as an alternative variable of illiquidity. As can be observed, the coefficient of *DARK×ZERORET* is significantly negative at the 1% level in both columns. It is in line with the stock liquidity mechanism which predicts a stronger negative effect of dark trading activities on firm value. In all the regressions in Panel A of Table X, we control for the individual effect of illiquidity variable and its coefficient (i.e., the coefficient of either *SPREAD* or *ZERORET*) is significantly negative at least at the 10% level. A negative effect of illiquidity on firm value is indicated here, and in other words a higher firm value for stocks with higher liquidity, which is consistent with the findings documented in Fang, Noe, and Tice (2009). By including illiquidity as a control variable, we demonstrate that the impact of dark trading activities on firm value is robust and not subsumed by the effect of liquidity.

Although block trading shows no effect on firm value in our baseline results, we run the interaction test of block trading and illiquidity as a robustness check. The corresponding regression specification is similar to Equation (16) except that the interaction term of dark trading and illiquidity variables (i.e., *DARK×SPREAD* or *DARK×ZERORET*) is substituted with the interaction term of block trading and illiquidity variables (i.e., *BLOCK×SPREAD* or *BLOCK×ZERORET*). The regression results are reported in Panel B of Table X. All the interaction terms of block trading and illiquidity variable are negative but not significant, which provides additional evidence to support the little impact of block trading on firm valuation.

5.3.2 Information Efficiency Mechanism

Under the information efficiency mechanism (Hypothesis 1A), the negative impact of dark trading activities on firm valuation is expected to be stronger for stocks with lower information efficiency (i.e., for stocks with higher information inefficiency). To test the information efficiency mechanism, we consider two alternative variables for measuring stock price informational efficiency: price delay ratio (*DELAY*) and absolute stock return autocorrelation (*AUTOCOR*), and both of them are widely used in prior studies (see, e.g., Comerton-Forde and Putninš, 2015; Brogaard, Li, and Xia, 2017). The price delay ratio (*DELAY*) is introduced by Hou and Moskowitz (2005) and measured by using 1 minus the ratio of R^2 with restrictions over R^2 without restrictions. The unrestricted R^2 is the R-squared obtained from regressing daily stock return on the concurrent market index return and lagged market returns up to 4 days. The restricted R^2 is the R-squared obtained from regressing daily stock return on the concurrent market index return only. Price delay ratio shows the level of information inefficiency of the firm and therefore a larger *DELAY* represents less informational efficiency in stock prices. The second information efficiency variable is *AUTOCOR* estimated as an absolute value of autocorrelation in daily stock returns.

When information efficiency increases, stock prices incorporate information in a more rapid manner and there would exist less serial correlation in stock returns. Both positive and negative return autocorrelation reflects informational inefficiency and a larger *AUTOCOR* indicates less informational efficiency in stock prices. To test the information efficiency mechanism and examine the robustness of our baseline findings, we run the interaction regressions of firm valuation as specified below:

$$Q_{i,t} = \alpha + \beta_1 DARK_{i,t-1} + \beta_2 BLOCK_{i,t-1} + \beta_3 DELAY_{i,t-1} \text{ (or } \beta_3 AUTOCOR_{i,t-1}) + \beta_4 DARK_{i,t-1} \times$$

$$DELAY_{i,t-1} \text{ (or } \beta_4 DARK_{i,t-1} \times AUTOCOR_{i,t-1}) + \gamma_1 SIZE_{i,t-1} + \gamma_2 TURNOVER_{i,t-1} + \gamma_3 IO_{i,t-1}$$

$$+\gamma_4 ANALYST_{i,t-1} + \gamma_5 LTD_{i,t-1} + \gamma_6 CAPX_{i,t-1} + \gamma_7 IDIO_{i,t-1} + \gamma_8 DIVD_{i,t-1} + \gamma_9 ROA_{i,t-1} +$$

$INDUSTRY_i + YEAR_{t-1} + \varepsilon$

(17)

$$Q_{i,t} = \alpha + \beta_1 DARK_{i,t-1} + \beta_2 BLOCK_{i,t-1} + \beta_3 DELAY_{i,t-1} \text{ (or } \beta_3 AUTOCOR_{i,t-1}) + \beta_4 BLOCK_{i,t-1} \times DELAY_{i,t-1} \text{ (or } \beta_4 BLOCK_{i,t-1} \times AUTOCOR_{i,t-1}) + \gamma_1 SIZE_{i,t-1} + \gamma_2 TURNOVER_{i,t-1} + \gamma_3 IO_{i,t-1} + \gamma_4 ANALYST_{i,t-1} + \gamma_5 LTD_{i,t-1} + \gamma_6 CAPX_{i,t-1} + \gamma_7 IDIO_{i,t-1} + \gamma_8 DIVD_{i,t-1} + \gamma_9 ROA_{i,t-1} + INDUSTRY_i + YEAR_{t-1} + \varepsilon$$

(18)

where $Q_{i,t}$ is the dependent variable measured as the Tobin's Q for firm i in year t, $DELAY_{i,t-1}$ and $AUTOCOR_{i,t-1}$ are alternative measures of information inefficiency for firm i in year $t-1$, and all the explanatory variables are lagged one year to address the concern of reverse causality. *DARK* and *BLOCK* stand for measures of dark trading and block trading, respectively. $DARK \times DELAY$ is the interaction term of dark trading and price delay ratio. $DARK \times AUTOCOR$ is the interaction term of dark trading and absolute value of return autocorrelation. $BLOCK \times DELAY$ ($BLOCK \times AUTOCOR$) is the interaction term of block trading and *DELAY* (*AUTOCOR*). Control variables of the baseline specification are included as well as industry and year fixed effects. Under the information efficiency mechanism (H1A), we expect the interaction term of *DARK* and variable of information inefficiency to have a negative effect (i.e., $\beta_4 < 0$ in Equation (17)), reflecting a stronger negative effect of *DARK* on firm value for stocks with poorer informational efficiency.

The regression results of estimating Equation (17) are reported in Panel A of Table XI. Although the interaction term of *DARK* and variable of information inefficiency (i.e., either $DARK \times DELAY$ or $DARK \times AUTOCOR$) has a negative coefficient in three out of the four columns, its coefficient is always insignificant. It indicates that the effect of dark trading activities on firm value does not vary with the level of stock price informational efficiency, which does not support the information efficiency mechanism (Hypothesis 1B). In the literature, theoretical models yield conflicting predictions about the impacts of dark trading on informational efficiency. For instance, Ye (2010) argues that the existence of dark venue enables informed traders to scale back the aggressiveness of their trading in the lit market in order to make larger profits in the dark. In contrast, Zhu (2014) argues that the lit market is attractive enough to informed traders and uninformed traders who will be more likely to trade in the dark. We also find inconclusive evidence to support information efficiency as the underlying mechanism for dark trading to affect firm value. Panel B of Table XI reports the results of estimating Equation (18) and the interaction term of *BLOCK* and variable of information inefficiency is always insignificant as expected. It confirms the little impact that block trading activities have on firm value.

Insert Table XI Here

5.3.3 Corporate Governance Mechanism

Under the corporate governance mechanism (Hypothesis 1C), the negative effect of dark trading activities on firm valuation is expected to be stronger for firms with higher blockholder ownership. Following Brogaard, Li, and Xia (2017), we employ two measures to capture governance: blockholder ownership (*BLOCKO*) and number of blockholders (*NBLOCK*), calculated using Thomson Reuters Ownership database. Blockholders refer to institutional investors who hold at least 5% of total common shares outstanding, and they play an important role in corporate governance as large shareholders. In our analysis, *BLOCKO* measures the aggregate percentage ownership of blockholders and *NBLOCK* is the number of blockholders. To test the underlying mechanism related to blockholders and examine the robustness of our baseline findings, we consider the interaction regressions as specified below:

$$Q_{i,t} = \alpha + \beta_1 DARK_{i,t-1} + \beta_2 BLOCK_{i,t-1} + \beta_3 BLOCKO_{i,t-1} \text{ (or } \beta_3 NBLOCK_{i,t-1}) + \beta_4 DARK_{i,t-1} \times BLOCKO_{i,t-1} \text{ (or } \beta_4 DARK_{i,t-1} \times NBLOCK_{i,t-1}) + \gamma_1 SIZE_{i,t-1} + \gamma_2 TURNOVER_{i,t-1} + \gamma_3 IO_{i,t-1} + \gamma_4 ANALYST_{i,t-1} + \gamma_5 LTD_{i,t-1} + \gamma_6 CAPX_{i,t-1} + \gamma_7 IDIO_{i,t-1} + \gamma_8 DIVD_{i,t-1} + \gamma_9 ROA_{i,t-1} + INDUSTRY_i + YEAR_{t-1} + \varepsilon \tag{19}$$

$$Q_{i,t} = \alpha + \beta_1 DARK_{i,t-1} + \beta_2 BLOCK_{i,t-1} + \beta_3 BLOCKO_{i,t-1} \text{ (or } \beta_3 NBLOCK_{i,t-1}) + \beta_4 BLOCK_{i,t-1} \times BLOCKO_{i,t-1} \text{ (or } \beta_4 BLOCK_{i,t-1} \times NBLOCK_{i,t-1}) + \gamma_1 SIZE_{i,t-1} + \gamma_2 TURNOVER_{i,t-1} + \gamma_3 IO_{i,t-1} + \gamma_4 ANALYST_{i,t-1} + \gamma_5 LTD_{i,t-1} + \gamma_6 CAPX_{i,t-1} + \gamma_7 IDIO_{i,t-1} + \gamma_8 DIVD_{i,t-1} + \gamma_9 ROA_{i,t-1} + INDUSTRY_i + YEAR_{t-1} + \varepsilon \tag{20}$$

where $Q_{i,t}$ is the dependent variable of Tobin's Q measured for firm *i* in year *t*, $DARK_{i,t-1}$ and $BLOCK_{i,t-1}$ are measures of dark trading and block trading for firm *i* in year *t-1*, $BLOCKO_{i,t-1}$ and $NBLOCK_{i,t-1}$ are blockholder ownership and number of blockholders for firm *i* in year *t-1*, and all the explanatory variables are lagged one year to address the concern of reverse causality. *DARK* × *BLOCKO* (*BLOCK* × *BLOCKO*) is the interaction term of dark (block) trading and blockholder ownership. *DARK* × *NBLOCK* (*BLOCK* × *NBLOCK*) is the interaction term of dark (block) trading and number of blockholders. Control variables are included the same as in the baseline specifications, while *INDUSTRY* and *YEAR* stand for industry and year fixed effects. The regression results of estimating Equation (19) are reported in Panel A of Table XII.

The coefficient of the interaction term of *DARK* and blockholder variable is insignificant in all four columns. It shows little evidence for supporting the corporate governance mechanism. As argued in Edmans, Fang, Zur (2013), liquidity as an indicator of market quality facilitates block formation and encourages governing via trading (exit), but on the other hand liquidity weakens blockholders' incentives for active intervention (voice). The offsetting relationships between market quality and corporate governance suggest that the effect of dark trading activities on firm valuation could be weakened or strengthened by blockholder ownership, which possibly explains our insignificant results.

Insert Table XII Here

The regression results of estimating Equation (20) are reported in Panel B of Table XII. *BLOCK*'s individual effect and interaction effect with blockholder variable are insignificant in all columns, although *DARK*'s individual effect remains significantly negative. It consistently supports the baseline findings on the detrimental effect of dark trading on firm value and the little relationship between block trading and firm value.

5.3.4 Additional Analysis on Mechanisms

In the previous analyses, we allow the effect of dark trading on firm value to vary with variable that is related to stock liquidity, or information efficiency, or corporate governance, and adopt interaction regressions to test the underlying mechanism(s). We document a more pronounced effect of dark trading in stocks with lower liquidity, although little evidence is found to support the information efficiency or corporate governance mechanism. For additional evidence on the underlying mechanism, we here adopt a difference-in-differences approach following Brogaard, Li, and Xia (2017) to test the changes in stock liquidity, information efficiency, and blockholder ownership in the matched sample constructed in Section 5.2.4. In particular, we use the removal of the ten-second rule on November 30, 2009 as an exogenous event because dark trading activities are demonstrated to significantly increase after the event while the event is exogenous with respect to firm valuation. Our adoption of the difference-in-differences approach overcomes the concern of reverse causality and endogeneity in testing the underlying mechanism. On the other hand, it offers direct tests on the long-term impacts of dark trading on liquidity, information efficiency, and blockholder ownership at the firm level.[78]

Following Section 5.2.4 and Table IX, we rank all sample firms based on their changes in dark trades surrounding the rule removal, and select the top 30% of the firms as treatment group and the bottom 30% of the firms as control group. We then run a probit model with the dependent variable being a dummy variable that is set to one for the firm in the treatment group and 0 in the control group. Propensity scores are used as predicted probabilities to match firms in two groups by closest propensity score match. We consider average quoted bid-ask spread (*SPREAD*) and percentage of days with zero returns (*ZERORET*) as variables of illiquidity, price delay ratio (*DELAY*) and absolute return autocorrelation (*AUTOCOR*) as variables of information inefficiency, and blockholder ownership (*BLOCKO*) and number of blockholders (*NBLOCK*) as variables of blockholder ownership. Table XIII reports the average variables of *SPREAD*, *ZERORET*, *DELAY*, *AUTOCOR*, *BLOCKO*, and *NBLOCK* in the matched treatment

[78] Although prior studies document evidence of liquidity, information efficiency, and blockholder ownership affecting firm valuation (see, e.g., Thomsen, Pedersen, and Kvist, 2006; Fang, Noe, Tice, 2009; Lang, Lins, and Maffett, 2012), direct tests do not exist regarding the impacts of dark trading on liquidity, information efficiency, and blockholder ownership based on firm-year observations.

and control groups in the year before the event (i.e., in 2008) and in the year after the event (i.e., in 2010), respectively, as well as difference-in-differences estimator of the variables and their corresponding t-statistics and p-values. The difference-in-differences estimator of both illiquidity variables (i.e., *SPREAD* and *ZERORET*) are significantly positive at the 1% level, while both variables increases (decreases) after the event in the treatment (control) group. It indicates a significant increase (decrease) in illiquidity (liquidity) in the treatment group after the removal of the ten-second rule. Combined with the findings in Panel E of Table IX about firm valuation, our results suggest firms experiencing a drop in firm valuation due to higher dark trading activities undermining stock liquidity.[79] The difference-in-differences estimators of both *DELAY* and *AUTOCOR* are insignificant, showing similar changes in information efficiency for the treatment and control groups around the exogenous event. It consistently excludes information efficiency as the underlying mechanism for dark trading to affect firm valuation.

Insert Table XIII Here

Interestingly, the difference-in-differences estimators of blockholder ownership variables (i.e., *BLOCKO* and *NBLOCK*) are significantly positive at the 1% level, while the variables

[79] The matched treatment and control groups have very similar firm characteristics and dark trading activities prior to the removal of the ten-second rule but experience a different degree of change in dark trading activities after the event. Panel E of Table IX shows that firms in the treatment group experience a more significant decrease in valuation after the ten-second rule has been removed compared to the control group. Fang, Noe, and Tice (2009) document that stock liquidity improves firm valuation. Given that Table XIII shows that firms in the treatment group experience a more significant decrease in stock liquidity, it demonstrates stock liquidity as the underlying mechanism whereby dark trading activities harm firm valuation.

decrease after the exogenous event in both treatment and control groups. It shows that the treatment group experiences a smaller decrease in blockholder ownership around the event compared to the control group, revealing a positive effect of dark trading activities on blockholder ownership. Given that Table XII find little evidence of blockholder ownership influencing the relationship between dark trading and firm valuation, our results suggest that the change in blockholder ownership induced by dark trading does not translate to firm valuation. Both stock liquidity and blockholder ownership are shown to be influenced by dark trading activities in the difference-in-differences tests.

5.3.5 Residual Effect of Dark Trading on Firm Valuation

While we provide evidence supporting two possible underlying mechanisms through which dark trading affects firm valuation, it is unclear whether there exists a residual or direct effect of dark trading on firm valuation beyond the effects taking place through the two mechanisms of stock liquidity and blockholder ownership. In other words, it remains to determine whether dark trading affects firm valuation only through these two underlying mechanisms or in a more direct way.[80] As argued in He and Tian (2013), disentangling the direct versus the indirect effect of dark trading enables us to test whether the causal relationship between dark trading and firm valuation identified in this thesis is merely a compilation of some established facts or goes beyond the existing literature to suggest a novel role of dark

[80] Although we find little evidence to support stock price informational efficiency as a possible underlying mechanism for dark trading to affect firm valuation, we do examine the residual effect of dark trading on firm valuation after controlling for all three possible mechanisms and obtain qualitatively similar results.

trading in affecting firm valuation.[81]

To examine the residual effect of dark trading on firm valuation, we perform a regression analysis in the difference-in-differences framework established in Section 5.2.4 that relies on a quasi-natural experiment related to dark trading (i.e., the removal of the ten-second rule in 2009). To construct the matched sample, we rank all sample firms based on their changes in dark trades surrounding the rule removal, and select the top 30% of the firms as treatment group and the bottom 30% of the firms as control group. We then run a probit model with the dependent variable being a dummy variable that is set to one for the firm in the treatment group and 0 in the control group. Propensity scores are used as predicted probabilities to match firms in two groups by closest propensity score match.

The difference-in-differences estimator of firm valuation captures the causal effect of dark trading on firm valuation. Following He and Tian (2013) that examine the residual effect of financial analysts on firm innovation, we test whether the difference-in-differences estimator of firm valuation is purely driven by the two underlying mechanisms of stock liquidity and blockholder ownership, or there exists a statistically significant component that cannot be fully absorbed by the two mechanisms. In particular, we modify the difference-in-differences regression specification in Equation (15) and directly control for the two mechanisms by estimating the following model based on the matched sample:

$$Q_{i,t} = \alpha + \beta_1 TREAT_i \times AFTER_t + \beta_2 TREAT_i + \beta_3 AFTER_t + \gamma_1 SPREAD_{i,t-1} \text{ (or } \gamma_1 ZERORET_{i,t-1})$$

[81] It is documented that stock liquidity and blockholder ownership affect firm valuation in the literature. For instance, Fang, Noe, and Tice (2009) find that firms with liquid stocks perform better. Brockman and Yan (2009) show a negative relationship between blockholder ownership and firm performance.

$$+\gamma_2 BLOCKO_{i,t-1}\ (\text{or } \gamma_2 NBLOCK_{i,t-1}) + INDUSTRY_i + \varepsilon,$$

(21)

where *TREAT* is a dummy variable equal to one (zero) if a firm is in the treatment (control) group, *AFTER* is a dummy variable equal to one for 2010 (post-event year) and zero for 2008 (pre-event year), and *TREAT×AFTER* is the interaction between these two variables. To proxy for the two underlying mechanisms, we consider average quoted bid-ask spread (*SPREAD*) and percentage of days with zero returns (*ZERORET*) as variables of illiquidity, and blockholder ownership (*BLOCKO*) and number of blockholders (*NBLOCK*) as variables of blockholder ownership. The key variable of interest in Equation (21) is the difference-in-differences estimator β_1 (i.e., the coefficient of $TREAT_i \times AFTER_t$). If there exists a residual treatment effect of dark trading on firm valuation, β_1 would continue to be negative and significant even after controlling for the two underlying mechanisms. If firm valuation is related to dark trading only through the two mechanisms, β_1 would lose its significance when we control for the two mechanisms.

The regression results of estimating Equation (21) are reported in Table XIV. In Panel A, industry fixed effects are constructed based on 2-digit GICS code (*Industry1*). The coefficient of *TREAT×AFTER* (i.e., β_1) is significantly negative at the 1% level in Column 1 without controlling for the underlying mechanism. It indicates a significant reduction in firm valuation caused by the removal of the ten-second rule, consistent with the causal effect of dark trading in reducing firm valuation. In Columns 2 to 5 where variables of stock liquidity and blockholder ownership are controlled for, the coefficient of *TREAT×AFTER* remains significantly negative at the 1% level although its estimate and t-statistics are reduced in magnitude compared to Column 1. Specifically, the coefficient of *TREAT×AFTER* ranges from -0.887 to -1.062 in Columns 2 to 5, which reflects a drop of 7.57% to 22.8% from the benchmark difference-in-differences estimator of -1.149 in Column 1.[82] It suggests two things: firstly, that the two underlying mechanisms of stock liquidity and blockholder ownership can explain up to 22.8% of the total effect of dark trading on firm valuation; and secondly, there exists a significant residual or direct effect for dark trading as influencing firm valuation.

Insert Table XIV Here

In Panel B, industry fixed effects are constructed based on General Industry Classification (*Industry2*) and the coefficient of *TREAT×AFTER* remains highly significant after controlling for the variables related to stock liquidity and blockholder ownership. It confirms a significant causal effect of dark trading on firm valuation even after controlling for its dependence on the two economic mechanisms. Our results suggest that while the underlying mechanisms could explain a significant portion of the causal effect of dark trading on firm valuation, there is a sizable direct or residual effect of dark trading on firm valuation. It is possible that unidentified economic mechanisms are measured as a direct effect in our analysis. In unreported robustness tests, we control for other variables in Equation (21), for instance variables related to stock price informational efficiency, or control for all possible mechanisms, and obtain qualitatively similar results.

In the empirical analysis for the study of firm default risk to be reported in Chapter 6, we find that dark trading activities are positively associated with firm default risk. As firms with higher default risk tend to have poorer performance and lower valuation, the negative

[82] We have (-0.887-(-1.149))/(-1.149)=-0.228=-22.8% and (-1.062-(-1.149))/(-1.149)=-0.0757=-7.57%.

relationship between dark trading and firm value could simply be a direct result of the firm default risk effect. To address a mechanical relationship between default risk increasing and, therefore, firm value decreasing, we further adopt firm default risk measured by one-year or five-year expected default frequency (*EDF_1y* or *EDF_5y*) as an additional control in the difference-in-differences regression specified in Equation (21) and report the results in Panels C to F of Table XIV. The coefficient of *TREAT×AFTER* remains significantly negative at the 1% level in all specifications considered although its estimate and t-statistics are slightly reduced in magnitude compared to their counterparts in Panels A and B. For instance, the coefficient of *TREAT×AFTER* is -1.190 in Column 1 of Panel C, which reflects a drop of 3.57% from the benchmark difference-in-differences estimator of -1.149 in Column 1 of Panel A. It demonstrates there exists a substantial direct effect for dark trading to affect firm value which is not through firm default risk.

5.4 Concluding Remarks

One of the most substantial changes in financial markets during the past decade is the emergence of dark pools which allows orders matched without providing any pre-trade transparency. An increasing number of trading activities are executed in dark pools. Block orders are managed by upstairs brokers without order details revealed to the market and executed outside of dark pools. Using a sample of Australian stocks for the years 2005-2015, we explore whether dark trading and block trading improves, harms, or has no effect on firm valuation as measured by a firm's Tobin's Q ratio. We find that dark trading activities decrease firm valuation, although the effect of block trading activities is not significant. The negative effect of dark trading is economically meaningful. A one-standard-deviation increase in the dark trading variable leads to firm value reduced over 14% of its mean. Our findings are robust to various endogeneity tests. To identify the causal effect of dark trading on firm valuation, we examine the impact of exogenous event to dark and block trading activities through a two-stage least squares instrument variable approach and a difference-in-differences approach. An increase in dark trading activities surrounding the exogenous event compromises firm performance, indicating dark trading does have a causal effect.

We explore three mechanisms through which dark trading can harm firm valuation including affecting stock liquidity, stock price informational efficiency, and corporate governance by blockholders. Although the relationship between dark trading and firm valuation does not vary with informational efficiency or blockholder ownership, we find that the effect of dark trading on firm valuation is stronger for firms with lower liquidity. By adopting the difference-in-differences approach, we further document a detrimental impact of dark trading activities on stock liquidity. It indicates dark trading harms firm valuation by reducing stock liquidity. The reduced stock liquidity reflects the high level of non-execution risk associated with dark trading. Overall, we provide evidence of dark trading exerting a negative effect on firm valuation, revealing a real effect of the emergence of dark pools. Block trading as an old form of dark trading is managed by upstairs brokers and has a lower level of non-execution risk compared to dark trading. We find little evidence of block trading affecting firm valuation. Taken together, we reveal a real adverse effect of dark trading activities in terms of reducing firm valuation.

Chapter 6

Empirical Results for the Study of Firm Default Risk

6.1 Empirical Results of Baseline Regressions

In the baseline specification of dark trading impacts on default risk, we estimate Equation (7) by using pooled OLS regression and report the results in Panel A of Table XV. The dependent variable is either one-year or five-year expected default frequency (*EDF_1y* or *EDF_5y*). *DARK* indicates measure of dark trading activities and is lagged by one year together with control variables to reduce the concern of reverse causality. In Column 1, fixed effects are not included and the estimated coefficient of *DARK* is 0.003 and significantly positive at the 1% level. We include industry fixed effects constructed based on 2-digit GICS code (GICS) in Column 2 and control for both industry and year fixed effects in Column 3. The effect of *DARK* remains significantly positive at least at the 5% level in both specifications. Our results support the third hypothesis (H3) that dark trading activities increase firm default risk.

The impact of dark trading activities is also economically meaningful. Let us take Column 3 as an example. A one-standard-deviation increase in *DARK* increases *EDF_1y* by 25.88% of its mean.[83] Comparing the results in Columns 1 to 3, we find that the significance level of *DARK* drops dramatically when year fixed effects are included. In particular, the t-statistics of *DARK* is 8.746 and 9.952 in Columns 1 and 2 and reduces to 2.465 in Column 3. Since year fixed effects are included to control for economy-wide shocks, our results suggest macroeconomic factors as important determinants of firm default risk. In Columns 4 to 6, we report the regression results of the five-year expected default frequency (*EDF_5y*). The

[83] Panel B of Table III shows that the sample standard deviation of *DARK* is 7.341 and the sample mean of *EDF_1y* is 0.085. As the regression coefficient of *DARK* is 0.003, we have 0.003×7.341=0.022 and 0.022/0.085=0.2588.

regression coefficient of *DARK* is positive and significant at the 1% level without controlling for fixed effects in Column 4 and remains highly significant when industry fixed effects are included in Column 5. Even when we additionally control for year fixed effects in Column 6, the effect of *DARK* is significantly positive and a one-standard-deviation increase in *DARK* increases *EDF_5y* by 11.85% of its mean.[84] It indicates that the positive effect of dark trading activities on firm default risk is robust even when we extend the evaluation horizon of default risk from one year to five years.

Insert Table XV Here

Panel B of Table XV examines the effect of block trading (*BLOCK*) on firm default risk (i.e., *EDF_1y* or *EDF_5y*) by estimating Equation (8). The coefficient of *BLOCK* is significantly positive in five out of the six columns, although the coefficient of *BLOCK* on *EDF_5y* becomes insignificant when both industry and year fixed effects are included in Column 6. In Panel C of Table XV, we report the regression results of estimating Equation (9) to test both effects of dark trading (*DARK*) and block trading (*BLOCK*) on firm default risk. The coefficient of *DARK* is significantly positive across all six columns, while the coefficient of *BLOCK* is always insignificant. It shows that the effect of block trading on firm default risk is subsumed by the effect of dark trading and there is no incremental effect for block trading to explain default risk. In other words, we find little evidence for block trading activities to influence a firm's creditworthiness. On the other hand, the positive effect of *DARK* remains

[84] Panel B of Table III shows that the sample standard deviation of *DARK* is 7.341 and the sample mean of *EDF_5y* is 0.248. As the regression coefficient of *DARK* is 0.004, we have $0.004 \times 7.341 = 0.0294$ and $0.0294/0.248 = 0.1185$.

significant even after controlling for the effect of *BLOCK*, which is consistent with our third hypothesis (H3) that dark trading activities increase firm default risk.[85]

The effect of dark trading activities is also economically significant. For instance, in the regressions with both industry and year fixed effects included (i.e., in Columns 3 and 6), a one-standard-deviation increase in *DARK* leads to the one-year expected default frequency increased by 17.29% of its mean and the five-year expected default frequency increased by 11.85% of its mean.[86] The emergence of dark pools is shown to influence many aspects of market quality, such as trading costs, price impacts, execution risk, stock liquidity, information asymmetry (see, e.g., Gresse, 2006; O'Hara and Ye, 2011; Zhu, 2014; Foley and Putninš, 2016). We show that dark trading activities can help to predict the likelihood of firm default, revealing a long-term impact of dark trades. Block trades exist before dark venues appear and they are executed through upstairs brokers. As upstairs brokers can serve as information repositories to tap into additional liquidity and signal trading motives, the impacts of block trades on market tend to be smaller compared to dark trades (Grossman, 1992; Comerton-Forde and Putninš, 2015). We find little evidence of block trading activities affecting the risk of firm default.

As reported in Table XV, some of the control variables are highly significant in the regressions of baseline specification. The expected default probability is negatively significant related with market value of equity at the 1% level across all the specifications, which indicates

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[85] In unreported robustness tests, we further control for analyst coverage (i.e., the *ANALYST* variable defined in Panel A of Table I.), our results remain qualitatively similar.

[86] Panel B of Table III shows that the sample standard deviation of *DARK* is 7.341 and the sample mean of *EDF_1y* (*EDF_5y*) is 0.085 (0.248). As the regression coefficient of *DARK* in Column 3 (Column 6) is 0.002 (0.004), we have 0.002×7.341=0.0147 (0.004×7.341=0.0294) and 0.0147/0.085=0.1729 (0.0294/0.248=0.1185).

that firms with higher market value of equity (i.e., larger firms) have lower default risk. The estimated coefficient of *Ln(DEBT)* is significantly positive at the 1% level. Default occurs when a firm is unable to meet its debt obligations or when its asset value falls below the debt value, and therefore the documented positive relationship between debt value and default is as expected. Default risk is also negatively significant correlated with inverse of annualized stock return volatility at the 1% level. It suggests that firms with higher stock volatility (i.e., firms with higher risk) are more likely to default. Excess return (*EX_RET*) and return of asset (*ROA*) wield a negative effect on firm default risk, although they are not always significant. Default risk tends to decrease with stock performance and firm profitability. The relationships between control variables and default probability are largely in line with prior default risk studies such as Bharath and Shumway (2008) and Brogaard, Li, and Xia (2017).

6.2 Endogeneity and Reverse Causality

In our baseline regressions, we lag explanatory variables and include control variables and industry and year fixed effects to mitigate the concerns of reverse causality and omitted variables. To further address the concern of endogeneity, we adopt 2SLS regressions and difference-in-differences test in this section.

6.2.1 Two-Stage Least Squares (2SLS) Regressions

Following Comerton-Forde and Putninš (2015), we exploit the variation in dark trading activities around two exogenous changes in market structure through an instrumental variable estimation and assess the effect of dark trading activities on firm default risk. Specifically, we instrument for dark trading with two indicators of market structure changes. The first indicator

$D^{rule\ remove}$ is constructed based on the removal of the ten-second rule on 30 November 2009, equals to 1 if the fiscal year ending date of the firm occurs after the rule removal and 0 otherwise. The ten-second rule requires the ASX broker to place an order in the CLOB for ten seconds before executing dark trades, and its removal makes execution of dark trades easier. The second indicator $D^{fee\ reduce}$ is constructed based on the reduction of ASX trading fees on 1 July 2010 and also captures the launch of Centre Point, the first exchange-based dark pool of ASX, in June 2010. $D^{fee\ reduce}$ equals to 1 if the fiscal year ending date of the firm occurs after 1 July 2010 and 0 otherwise. Our instrument variable estimation relies on the assumption that the two exogenous events do not directly affect firm default risk except through their impacts on dark trading activities, and this assumption is reasonable in our setting because both events are implemented by ASX to ease dark trades.

The first-stage regression of our 2SLS instrumental variable approach is specified in Equation (22) below. The variable of dark trading (*DARK*) is regressed on two instrumental variables, block trading variable, control variables of the baseline specification and industry fixed effects.[87]

$$DARK_{i,t} = \alpha + \beta_1 D_{i,t}^{rule\ remove} + \beta_2 D_{i,t}^{fee\ reduce} + \gamma_1 BLOCK_{i,t} + \gamma_2 Ln(EQUITY_{i,t}) + \gamma_3 Ln(DEBT_{i,t}) + \gamma_4 1/\sigma_{E_{i,t-1}} + \gamma_5 EX\_RET_{i,t} + \gamma_6 ROA_{i,t} + INDUSTRY_i + \varepsilon, \tag{22}$$

[87] Because block trading variable (*BLOCK*) shows little impact on firm default risk, we directly consider it as a control variable in the 2SLS test. It is different from the first study that both variables of dark and block trading (*DARK* and *BLOCK*) are predicted in the first-stage regressions. Our results remain qualitatively similar if both *DARK* and *BLOCK* are predicted in the first-stage regressions in the study of firm default risk.

where the dependent variable of dark trading $DARK_{i,t}$ is measured for firm i in year t, $D_{i,t}^{rule\ remove}$ is the dummy variable for the removal of the ten-second rule which equals to 1 if the end date of fiscal year t for firm i is after the date of rule removal (i.e., 30 November 2009) and 0 otherwise, $D_{i,t}^{fee\ reduce}$ is the dummy variable for the reduction of trading fees which equals to 1 if the end date of fiscal year t for firm i is after the date of trading fee reduction (i.e., 1 July 2010) and 0 otherwise, and both dummy variables serve as instrumental variables. The block trading variable $BLOCK_{i,t}$ is measured for firm i in year t. All the other control variables are measured for firm i in year t including natural logarithm of market value of equity (*Ln(Equity)*), natural logarithm of book value of debt (*Ln(Debt)*), inverse of annualized stock return volatility ($1/\sigma_E$), annual excess return (*EX_RET*), and ratio of net income to total asset (*ROA*). Industry fixed effects are constructed based on 2- digit GICS code (GICS). The first-stage regression specified in Equation (22) is estimated by OLS and then the fitted value (*PRE_DARK*) is used as an independent variable in the second-stage regression of firm default risk. The dependent variable of the second-stage regression is the one-year or five-year expected default frequency (*EDF_1y* or *EDF_5y*), and it is regressed on fitted value of dark trading, block trading variable, the same set of control variables as in the baseline specification and industry fixed effects. To mitigate the concern of reverse causality, all the independent variables are lagged. In particular, the second-stage regression of firm default risk is specified below:

$$EDF\_1y_{i,t}\ (EDF\_5y_{i,t}) = \alpha + \beta_1 PRE\_DARK_{i,t-1} + \gamma_1 BLOCK_{i,t-1} + \gamma_2 Ln(EQUITY_{i,t-1}) + \gamma_3 Ln(DEBT_{i,t-1}) + \gamma_4 1/\sigma_{E_{i,t-1}} + \gamma_5 EX\_RET_{i,t-1} + \gamma_6 ROA_{i,t-1} + INDUSTRY_i + \varepsilon, \quad (23)$$

where $EDF\_1y_{i,t}$ ($EDF\_5y_{i,t}$) is the one-year (five-year) expected default frequency for firm i in year t, $PRE\_DARK_{i,t-1}$ is the fitted value of dark trading variable for firm i in year $t-1$ from estimating the first-stage regression as specified in Equation (22) and $BLOCK_{i,t-1}$ is the block trading variable for firm i in year $t-1$. Consistent with the first-stage regression, we control for a set of firm characteristics and industry fixed effects.

Column 1 of Table XVI reports the results of the first-stage regression. The coefficients of both instrumental variables (i.e., $D^{rule\ remove}$ and $D^{fee\ reduce}$) are 9.608 and 1.332 and significantly positive at the 1% level. It indicates that dark trading activities increase substantially after both exogenous events.[88] The high first-stage F-statistic strongly indicates that our instruments satisfy the relevance condition. Results of the second-stage regressions are reported in the other two columns. In the regression of the one-year expected default frequency (*EDF_1y*), the coefficient of the predicted value of dark trading (*PRE_DARK*) is significantly positive at the 1% level. It is consistent with the third hypothesis (H3) which posits that dark trading activities increase firm default risk. Even when the evaluation horizon of the default risk is extended from one year to five year, the effect of *PRE_DARK* remains significantly positive at the 10% level.

Insert Table XVI Here

6.2.2 Difference-in-Differences Test

In this section we use the difference-in-differences approach to mitigate the concern of

[88] The regression coefficient of $D^{rule\ remove}$ ($D^{fee\ reduce}$) is 9.608 (1.332) and the sample mean of *DARK* is -5.546 as shown in Panel B of Table III. When the dummy variable changes from 0 to 1, *DARK* is increased by 9.608 (1.332) which equals to 9.608/5.546=1.732 (1.332/5.546=0.24) of its mean.

endogeneity. According to the first-stage regression results reported in Table XVI, the removal of the ten-second rule has a more pronounced effect on dark trading activities compared to the reduction of trading fees.[89] Therefore, we adopt the removal of the ten-second rule that occurs on November 30, 2009 as an exogeneous event for our difference-in-differences tests. We consider observations of two years; one is before the exogenous event while the other is after. The reverse causality and the potential omitted variables problem could be minimized due to the small possibility of significant changes in the short testing window (Fang, Noe, and Tice, 2009).

Following Fang, Tian, and Tice (2014) and Brogaard, Li, and Xia (2017), we form a treatment group and a control group by using propensity score matching. All sample firms are ranked based on the changes in dark trading variable (*DARK*) around the removal of the ten-second rule. The top 45% of the firms are formed as treatment group and the bottom 45% of the firms are formed as control group.[90] Then we regress a probit model in which a dependent dummy variable is equal to one if the firm is located in the top 45% (treatment group) and 0 if the firm is located in the bottom 45% (control group). The independent variables in the probit model are dark trading (*DARK*), block trading (*BLOCK*) and all the control variables in baseline specification, for example in Equation (7).

Propensity scores are then used as predicted probabilities to match firms in the treatment

[89] In Column 1 of Table XVI, the t-statistic of $D^{rule\ remove}$ is 51.303 and much larger than that of $D^{fee\ reduce}$ which is 14.586.

[90] We apply different thresholds in the two studies to demonstrate the robustness of the results, although the findings remain qualitatively similar if we consider 30% instead of 45% as the threshold.

group that represent a high dark trading increase because of the "10-second rule removal" and control group, which represents the lowest dark trading increase due to the abolition of the rule. Specifically, each firm in the top 45% is matched with firms in the bottom 45% by closest propensity score. After the matching procedure, we have 221 pairs of treatment-control groups and 442 matched observations in total. Table XVII reports the results of the difference-in-differences tests. Results of estimating the probit model based on the unmatched treatment and control groups are reported in Column 1 of Panel A. The model produces a pseudo R^2 of 7.15% and a chi-square test's p-value of less than 0.0001. In line with previous literature using difference-in-differences tests, our probit model specification captures a significant amount of variation in the choice variable. Following Fang, Tian, and Tice (2014) and Brogaard, Li, and Xia (2017), we use three diagnostic tests to verify the assumption in our difference-in-differences test.

Insert Table XVII Here

The first diagnostic test is the comparison between before-match probit model and after-match probit model. The results of estimating probit model based on the matched treatment and control groups (i.e., the after-match sample) are reported in Column 2 of Panel A. Compared with before-match probit model, the likelihood ratio in the after-match model is lower. Meanwhile, the significant estimates of the independent variables in the before-match probit model become much smaller in the after-match model and the variable of dark trading (*DARK*) is no longer statistically significant in the after-match model. Furthermore, the chi-square test's p-value is below 0.0001 for the before-match model and increases to 0.1410 in the after-match model. The same situation happens to pseudo R^2 which drops dramatically from

7.15% in the pre-match model to 1.95% in the after-match model. Our first diagnostic test suggests a weaker relationship between firm characteristic differentials of the treatment group and control group after the matching procedure.

The second diagnostic test is examining the difference of propensity scores between treatment group and control group. Panel B in Table XVII reports propensity score distribution of treatment group, control group, and differentials of two groups in the after-match sample. From the panel we could see the difference of two matched groups is very small. For example, the maximum of the distance between the propensity score of matched groups is only -0.128, and the average of the differential is only 0.003. Our second diagnostic test shows that the propensity scores of matched treatment group and control group are very similar.

The final diagnostic test examines the t-statistics of the differences in two groups' characteristics before the exogenous event of the ten-second rule removal. The results are reported in Panel C of Table XVII. The t-values of differences between treatment group and control group are largely not significant across the characteristics considered except for *Ln(EQUITY)* and $1/\sigma_E$ being significantly different at the 10% level and *Ln(DEBT)* being significantly different at the 5% level. Although the removal of the ten-second rule affects the two group differently, the difference in the variable of dark trading (*DARK*) is quite small (-0.066) between the groups and it is also statistically insignificant. It shows that the matched two groups have a similar level of dark trading before the exogenous event. Our third diagnostic test suggests that the propensity score matching method could restrain the potentially confounding firm differences known to affect firm default risk and also help to reduce the concerns that the differences are created by general time trend. The t-statistics of the differences in two groups' characteristics after the exogenous event are reported in Panel D of Table XVII. The difference in dark trading variable (*DARK*) changes from -0.066 to 0.534, and becomes statistically significant at the 1% level (t-value=4.973). The differentials in dark trading between Panel C and Panel D demonstrate that the removal of the ten-second rule as an exogenous event creates significant differences between the treatment and control firms.

Panel E of Table XVII shows the difference-in-differences estimator of firm default risk. We report the estimators and corresponding t-values of one-year expected default frequency (*EDF_1y*) and five-year expected default risk (*EDF_5y*) as measures of firm default risk. The changes in *EDF_1y* and *EDF_5y* from pre-event year (2008) to post-event year (2010) are calculated, respectively, for the treatment and control groups. The difference-in-differences estimator of *EDF_1y* (*EDF_5y*) is calculated as the gap between the change in *EDF_1y* (*EDF_5y*) for control group and the change in *EDF_1y* (*EDF_5y*) for treatment group, and we report its mean, t-statistic and p-value. In both treatment and control groups, *EDF_1y* (*EDF_5y*) decreases after the exogenous event reflecting the general time trend, which indicates that firm default risk drops substantially from 2008 to 2010. It is consistent with the onset of the GFC in 2007-2009 and the improved firm creditworthiness after the crisis. The difference-in-differences estimator of *EDF_1y* (*EDF_5y*) is 0.169 (0.199) and significantly positive at the 1% level. It shows that firms in the treatment group experience a much weaker reduction in default risk around the exogenous event (i.e., from 2008 to 2010) compared to firms in the control group, which supports the third hypothesis (H3) that dark trading activities increase firm default risk.

Panel F of Table XVII reports the results of estimating difference-in-differences regression based on the specification below.

$$EDF\_1y_{i,t}\ (EDF\_5y_{i,t}) = \alpha + \beta_1 TREAT_i \times AFTER_t + \beta_2 TREAT_i + \beta_3 AFTER_t + \gamma_1 BLOCK_{i,t-1} + \gamma_2 Ln(EQUITY_{i,t-1}) + \gamma_3 Ln(DEBT_{i,t-1}) + \gamma_4 1/\sigma_{E_{i,t-1}} + \gamma_5 EX\_RET_{i,t-1} + \gamma_6 ROA_{i,t-1} + INDUSTRY_i + \varepsilon \tag{24}$$

where $TREAT_i$ is a dummy variable equal to one (zero) if firm i is in the treatment (control) group, $AFTER_t$ is a dummy variable equal to one for 2010 (post-event year) and zero for 2008 (pre-event year), and $TREAT_i \times AFTER_t$ is the interaction between these two variables. The control variables are the same as those used in the probit model in Panel A of Table XVII. In addition, we control for block trading variable (*BLOCK*) and industry fixed effects. As shown in the regression of *EDF_1y* in Column 1 of Panel F, the interaction term (*TREAT×AFTER*) has a coefficient of 0.099 which is significantly positive at the 1% level. It indicates a larger increase in the one-year expected default frequency around the exogenous event for the firms in the treatment group compared to the firms in the control group, which is consistent with the positive impact of dark trading activities on firm default risk. In the regression of *EDF_5y* reported in Column 2, the interaction term (*TREAT×AFTER*) is significantly positive at the 1% level. It consistently supports the hypothesis of dark trading increasing firm default risk. Taken together, our findings in the baseline specifications remain robust in the difference-in-differences tests.

6.3 Additional Analyses to Control for the Effect of Firm Value

Default occurs when a firm is unable to meet its debt obligations or when its asset value falls below the debt value (Brogaard, Li, and Xia, 2017). In our first study of firm valuation, we show that dark trading has negative impacts on firm valuation as measured by Tobin's Q. As firms with poorer performance (i.e., with lower valuation) are more likely to default, the positive relationship between dark trading and default probability could simply be a direct result of the firm value effect. To address a mechanical relationship between firm value decreasing and, therefore, default risk increasing, we adopt additional analyses to take into account the effects of firm value in this section.

We first re-run our baseline regressions with Tobin's Q controlled for. Same as in the study of firm value, Tobin's Q (*Q*) is defined as market value of assets divided by book value of total assets, where the market value of assets equals to market value of equity plus book value of assets subtract book value of equity and balance sheet deferred taxes. We add *Q* as a control variable in the baseline specifications of Equations (7-9) and report the regression results in Table XVIII. As shown in Panel A, the coefficient of dark trading variable (*DARK*) on the one-year expected default frequency (*EDF_1y*) is always significantly positive at the 1% level no matter whether industry and/or year fixed effects are controlled for or not. In the regression of the five-year expected default frequency (*EDF_5y*), the coefficient of *DARK* is significantly positive at the 1% level without fixed effects or with industry fixed effects included. It remains significant at the 10% level when year fixed effects are further included. Panel C reports the regression results after controlling for the effect of block trading variable (*BLOCK*), and the positive effect of *DARK* remains significant on both *EDF_1y* and *EDF_5y*. The coefficient of *BLOCK* is not statistically significant in any columns of Panel C although it is significant in Panel B when year fixed effects are not included. It is consistent with our baseline finding that the impact of block trading is subsumed by the impact of dark trading. Although the regression coefficient of firm value (*Q*) is largely negative in the table reflecting lower default risk for firms with higher valuation, it is always insignificant, which indicates little impact of firm value on default risk in our sample. Taken together, Table XVIII demonstrates that the positive impact of dark trading on firm default risk remains robust after controlling for the effect of firm value.

Insert Table XVIII Here

To address the firm value effects, Brogaard, Li, and Xia (2017) test the baseline relationship in the framework of difference-in-differences regressions after controlling for the changes in Tobin's Q around the exogenous event. Following Brogaard, Li, and Xia (2017), we extend our difference-in-differences regressions specified in Panel F of Table XVII by including the interaction of *Q* changes and the after-event dummy variable ($\Delta Q \times AFTER$).[91] The removal of the ten-second rule in 2009 is adopted as the exogenous event. Any differential change in firm default risk due to a change in firm value could be captured by controlling for $\Delta Q \times AFTER$. The extended difference-in-differences regression is specified as follows:

$$EDF\_1y_{i,t}\ (EDF\_5y_{i,t}) = \alpha + \beta_1 TREAT_i \times AFTER_t + \beta_2 TREAT_i + \beta_3 AFTER_t + \beta 4 \Delta Q_i \times AFTER_t + \gamma_1 BLOCK_{i,t-1} + \gamma_2 Ln(EQUITY_{i,t-1}) + \gamma_3 Ln(DEBT_{i,t-1}) + \gamma_4 1/\sigma_{E_{i,t-1}} + \gamma_5 EX\_RET_{i,t-1} + \gamma_6 ROA_{i,t-1} + INDUSTRY_i + \varepsilon \quad (25)$$

where $TREAT_i$ is a dummy variable equal to one (zero) if firm *i* is in the treatment (control)

[91] ΔQ is the change of *Q* around the exogenous event by using *Q* in 2010 to minus *Q* in 2008. *AFTER* is a dummy variable equal to one for 2010 and zero for 2008. $\Delta Q \times AFTER$ is the interaction between these two variables.

group, $AFTER_t$ is a dummy variable equal to one for 2010 (post-event year) and zero for 2008 (pre-event year), and ΔQ_i denotes the change in Q of firm i from the pre-event year to the post-event year. We report the results of estimating the extended difference-in-differences regression on the matched sample in Table XIX. In the first two columns, the dependent variable is the one-year expected default frequency (*EDF_1y*) and the regression coefficient of $TREAT \times AFTER$ is significantly positive at the 1% level. It indicates that the treatment firms experience a larger increase in default risk after the exogenous event compared to the control firms. When the five-year expected default frequency (*EDF_5y*) is adopted as the dependent variable in Columns 3 to 4, the regression coefficient of $TREAT \times AFTER$ remains significantly positive at the 1% level. Meanwhile, the interaction term of $\Delta Q \times AFTER$ is insignificant in 3 out of the 4 columns. Our results demonstrate that the positive effect of dark trading on firm default risk is not through firm value. In other words, the relationship between dark trading and firm default risk is not mechanical.

Insert Table XIX Here

6.4 How Does Dark Trading Increase Firm Default Risk?

In this section we provide an analysis on the potential underlying mechanism(s) for dark trading activities to increase firm default risk. Dark trading activities are documented as influencing some aspects of market quality such as stock liquidity and information efficiency (see, e.g., Comerton-Forde and Putninš, 2015; Kwan, Masulis, and McInish, 2015; Foley and Putninš, 2016). In addition, blockholders' monitoring incentives are likely to be affected by market quality (Maug, 1998; Fang, Noe and Tice, 2009), and therefore can be related to dark trading activities. On the other hand, Brogaard, Li, and Xia (2017) examine the impact of stock liquidity on firm default risk and argue information efficiency and corporate governance (proxied by blockholder ownership) as the possible underlying mechanisms. To understand how dark trading increases firm default risk, we examine stock liquidity, information efficiency, and corporate governance as potential underlying mechanisms

Furthermore, we also test financial constraints as another possible underlying mechanism. Given the definition of financial constraints as frictions that prevent firms from funding their desired investments (Lamont, Polk, and Saaá-Requejo 2001; He and Ren, 2017), dark trading activities can potentially influence financial constraints of the firm through its impact on market quality. As argued in Khanna and Sonti (2004), informed traders factor the effect of their trades on managerial behavior into their trading strategy, which influences operating performance and financial constraints. Firms experiencing more financial constraints are more likely to default (He and Ren, 2017).[92]

6.4.1 Difference-in-Differences Tests on the Underlying Mechanisms

To test the underlying mechanisms, we use average quoted bid-ask spread (*SPREAD*) and percentage of days with zero returns (*ZERORET*) as measures of stock illiquidity, price delay ratio (*DELAY*) and absolute return correlation (*AUTOCOR*) as measures of stock price

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[92] Fazzari, Hubbard, and Petersen (1987), Almeida, Campello, and Weisbach (2004), and Acharya, Almeida, and Campello (2007) argue that spending on investment by financially constrained firms is more sensitive to cash flow than that by unconstrained firms. Cash shortages are more likely to precipitate corporate default for financially constrained firms. By contrast, this impact is insignificant when a firm is financially unconstrained (Davydenko, 2012). Based on these arguments, He and Ren (2017) conclude that a financially constrained firm is more prone to default than an unconstrained one.

informational inefficiency, and blockholder ownership (*BLOCKO*) and number of blockholders (*NBLOCK*) as measures of blockholder ownership. To measure financial constraints, we follow Hadlock and Pierce (2010) and He and Ren (2017) to adopt the SA index calculated as written below:[93]

$$SA = -0.737 \times SIZE + 0.043 \times SIZE^2 - 0.040 \times AGE, \tag{26}$$

where *SIZE* is the natural logarithm of market capitalization and *AGE* is the number of years since the firm is founded. More financially constrained firms have higher *SA* index, and there exists a quadratic relationship between firm size and financial constraints and a negative relationship between firm age and financial constraints. Younger firms are subject to more financial constraints and tend to have higher SA index.

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[93] There are two commonly used financial-constraint measures called KZ index (Kaplan and Zingales, 1997) and WW index (Whited and Wu, 2006). Hadlock and Pierce (2010) construct a new financial-constraint index called the SA index. They hand collected qualitative information that is closely related to firm financial constraints. Based on the qualitative information collected, they categorize firms' financial constraint statuses and estimate the ordered logit regressions of the financial-constraint category on the determinants of KZ index and WW index, respectively. The ordered logit regression results show that only two out of five determinants of the KZ index and three out of six determinants of the WW index have significant coefficients with predicted signs. The results cast doubt on the validity of using the KZ and WW indices as proxies for financial constraints. In developing a valid measure of financial constraint, Hadlock and Pierce (2010) sort firms by firm characteristics that are arguably associated with financial constraints and test the association between the sorting variables and the aforementioned financial-constraint category. They find evidence that only firm size and firm age are powerful in predicting a firm's financial constraint status. They further argue that firm size and firm age are relatively exogenous to a firm's financial choices compared to other firm characteristics. A new financial-constraint index called the SA index is created by simply use the two variables (size and age).

We here adopt a difference-in-differences test based on the matched sample constructed in Section 6.2.2 (Table XVII) to examine changes in the variables of the underlying mechanisms around the exogenous event of the removal of the ten-second rule in 2009. It also helps to mitigate the concern of endogeneity and reverse causality. In particular, we rank all sample firms based on their changes in dark trades surrounding the rule removal, and select the top 45% of the firms as treatment group and the bottom 45% of the firms as control group. We then run a probit model with the dependent variable being a dummy variable that is set to one for the firm in the treatment group and 0 in the control group. Propensity scores are used as predicted probabilities to match firms in two groups by closest propensity score match. Table XX reports the average variables of *SPREAD*, *ZERORET*, *DELAY*, *AUTOCOR*, *BLOCKO*, *NBLOCK*, and *SA* in the matched treatment and control groups in the year before the event (i.e., in 2008) and in the year after the event (i.e., in 2010), respectively, as well as difference-in-differences estimator of the variables and their corresponding t-statistics and p-values. The difference-in-differences estimator of both illiquidity variables (i.e., *SPREAD* and *ZERORET*) is significantly positive at the 1% level. It shows that firms in the treatment group experience a larger increase in stock illiquidity compared to firms in the control group, revealing a positive (negative) impact of dark trading on stock illiquidity (stock liquidity). The difference-in-differences estimator of *BLOCKO* (*NBLOCK*) is significantly positive at the 1% (5%) level. It indicates a positive impact of dark trading on blockholder ownership. However, the difference-in-differences estimator of variables related to information efficiency and the SA index is statistically insignificant, except for *AUTOCOR* of which difference-in-differences estimator is significantly positive at the 10% level. It presents weak evidence of dark trading reducing stock price informational efficiency and furthermore dark trading has little impact on financial constraints.

Insert Table XX Here

6.4.2 Relative Importance of the Identified Mechanisms

Both stock liquidity and blockholder ownership are shown to be affected by dark trading activities. To further examine through which mechanism dark trading impacts firm default risk, we run a “horse race” test to explain default risk following Brogaard, Li, and Xia (2017). In particular, the “horse race” test implements a standardized regression of default risk with both mechanisms examined together based on the matched sample. All the variables are standardized by subtracting their mean value and dividing the difference by their standard deviation. By using one of our dependent variables *EDF_1y* as an example, we first calculate the changing of *EDF_1y* from 2008 to 2010 and obtain *ΔEDF_1y*. Then we calculate the standardized *Δ EDF_1y* (labelled as *Δ EDF_1y* STD) by subtracting its mean value and dividing the difference by the standard deviation of *Δ EDF_1y*. All the variables are standardized by the same method.

The standardized dependent variable (*ΔEDF_1y* STD) is regressed on the standardized change of variables related to the two mechanisms (*ΔBLOCKO* STD, *ΔNBLOCK* STD, *ΔSPREAD* STD, *ΔZERORET* STD) along with standardized variables of block trading and control variables (*ΔBLOCK* STD, *ΔSIZE* STD, *ΔTURNOVER* STD, *ΔIO* STD, *ΔANALYST* STD, *ΔLTD* STD, *ΔCAPX* STD, *ΔIDIO* STD, *ΔDIVD* STD, *ΔROA* STD). The regression coefficient can then be interpreted as the impact of one-standard-deviation in the independent variable on the dependent variable, in terms of a standard deviation variation. The regression results are reported in Table XXI. In Panel A where *ΔEDF_1y* STD is adopted as the dependent variable, the regression coefficient of stock illiquidity variable (i.e., *ΔSPREAD* STD or *ΔZERORET* STD) is statistically significant at the 1% level across all columns. In contrast, the regression coefficient of blockholder ownership variable (i.e., *ΔBLOCKO* STD or *ΔNBLOCK* STD) is always insignificant. It reveals that stock liquidity is the underlying mechanism for dark trading activities affecting firm default risk. The role of stock liquidity is also economically substantial. For instance, the regression coefficient of *ΔSPREAD* STD (*ΔZERORET* STD) is -0.222 (-0.197) in Column 1 (Column 3), which indicates that one-standard-deviation decrease in *ΔSPREAD* (*ΔZERORET*) can lead to about 22.2% (19.7%) increase in the standard deviation of *ΔEDF_1y*. Our results indicate that stock liquidity is the underlying channel for dark trading to affect the one-year expected default frequency.

Insert Table XXI Here

In Panel B, we consider firm default risk over the five-year horizon and reports the regression results. The regression coefficient of stock illiquidity variable (i.e., *ΔSPREAD* STD or *ΔZERORET* STD) is statistically significant at least at the 5% level in all columns. In contrast, the regression coefficient of *ΔBLOCKO* STD is insignificant and that of *ΔNBLOCK* STD) is statistically significant at the 10% level, and both of them are much smaller in magnitude compared to the coefficient of stock illiquidity variable. It demonstrates that the stock liquidity channel better explains the five-year expected default frequency than the corporate governance channel.

6.4.3 Residual Effect of Dark Trading on Firm Default Risk

After testing the underlying mechanisms for dark trading to affect firm default risk, it remains unclear whether there exists a residual or direct effect of dark trading on firm default risk after taking into account the effects through the underlying mechanisms. For instance, Brogaard, Li, and Xia (2017) show that enhanced stock liquidity decreases default risk. We demonstrate that dark trading increases default risk through reducing stock liquidity and it remains to determine whether dark trading affects default risk only through affecting stock liquidity or in a more direct manner. In addition, although we show in Section 6.3 that the positive relationship between dark trading and firm default risk is not mechanical through the reduced firm value, it is likely for changes in firm value to partially explain the effect of dark trading on firm default risk. Following He and Tian (2013), we disentangle the direct versus the indirect effect of dark trading to test whether the causal relationship between dark trading and firm default risk goes beyond the existing literature, for instance Brogaard, Li, and Xia (2017). Furthermore, our study of firm valuation suggests a novel role of dark trading in affecting firm default risk.

To examine the residual effect of dark trading on firm default risk, we perform a regression analysis in the difference-in-differences framework established in Section 6.2.2. It relies on the removal of the ten-second rule in 2009 as an exogenous event to dark trading and considers a matched sample that have similar firm characteristics before the event but experience different changes in dark trading around the event. The difference-in-differences estimator of firm default risk captures the causal effect of dark trading on default risk. In Section 6.4.2, we find robust evidence of dark trading affecting stock liquidity and blockholder ownership. Although there only exists a weak relationship between dark trading and one of the variables related to information efficiency, we consider information efficiency as a third possible mechanism when examining the residual effect of dark trading on firm default risk.[94]

Following He and Tian (2013), we test whether there exists a statistically significant component in the difference-in-differences estimator of firm default risk that cannot be fully explained by the three mechanisms of stock liquidity, blockholder ownership, and information efficiency. We modify the difference-in-differences regression specified in Equation (24) and directly control for the three mechanisms by estimating the following model based on the matched sample:

$$EDF\_1y_{i,t}\ (EDF\_5y_{i,t}) = \alpha + \beta_1 TREAT_i \times AFTER_t + \beta_2 TREAT_i + \beta_3 AFTER_t + \gamma_1 SPREAD_{i,t-1}$$
$$(\text{or } \gamma_1 ZERORET_{i,t-1}) + \gamma_2 ZERORET_{i,t-1}\ (\text{or } \gamma_2 DELAY_{i,t-1})$$
$$+ \gamma_3 BLOCKO_{i,t-1}\ (\text{or } \gamma_3 NBLOCK_{i,t-1}) + INDUSTRY_i + \varepsilon, \qquad (27)$$

where *TREAT* is a dummy variable equal to one (zero) if a firm is in the treatment (control) group, *AFTER* is a dummy variable equal to one for 2010 (post-event year) and zero for 2008 (pre-event year), and *TREAT×AFTER* is the interaction between these two variables. To proxy for the three underlying mechanisms, we consider average quoted bid-ask spread (*SPREAD*) and percentage of days with zero returns (*ZERORET*) as variables of illiquidity, price delay measure (*DELAY*) and absolute stock return autocorrelation (*AUTOCOR*) as variables of information efficiency, and blockholder ownership (*BLOCKO*) and number of blockholders (*NBLOCK*) as variables of blockholder ownership. The key variable of interest in Equation (27) is the coefficient of $TREAT_i \times AFTER_t$. If evidence of a residual treatment effect of dark trading

[94] Our results remain qualitatively similar when the channel of information efficiency is excluded when examining the residual effect of dark trading on firm default risk.

on firm default risk exists, this coefficient would continue to be positive and significant even after controlling for the three underlying mechanisms. If firm default risk is related to dark trading only through the three mechanisms, β_1 would lose its significance when we control for the mechanisms.

The results of estimating Equation (27) are reported in Panels A and B of Table XXII for the regressions of *EDF_1y* and *EDF_5y*, respectively. In Panel A, the coefficient of *TREAT×AFTER* is significantly positive at the 1% level in Column 1 without controlling for the underlying mechanism. It indicates a significant increase in firm default risk caused by the removal of the ten-second rule. In Columns 2 to 9 where variables of stock liquidity, information efficiency, and blockholder ownership are controlled for, the coefficient of *TREAT×AFTER* remains significantly positive at the 1% level. Among the last six columns, the smallest coefficient of *TREAT×AFTER* is 0.156, which reflects a drop of 7.69% from the benchmark difference-in-differences estimator of 0.169 in Column 1. It suggests the three underlying mechanisms can explain up to 7.69% of the total effect of dark trading on the one-year expected default frequency. In Panel B where the five-year expected default frequency is the dependent variable, the coefficient of *TREAT×AFTER* is 0.199 and significant at the 1% level. In Columns 2 to 9, the coefficient of *TREAT×AFTER* remains significantly positive at the 1% level, and the smallest figure is 0.188 which corresponds to a drop of 5.52% from the benchmark difference-in-differences estimator of 0.199 in Column 1. Both panels demonstrate that there exists a significant residual or direct effect for dark trading to affect firm default risk after controlling for the underlying mechanisms. In unreported robustness tests, we control for all possible mechanisms and obtain qualitatively similar results.

$\boxed{\text{Insert Table XXII Here}}$

In Chapter 5, we demonstrate that dark trading reduces firm valuation. Firms with higher market valuation are less likely to default, and therefore firm value represents a possible channel for dark trading to increase firm default risk. To further understand the residual effect of dark trading, we extend the difference-in-differences regression specification in (27) to control for firm value:

$$EDF\_1y_{i,t}\ (EDF\_5y_{i,t}) = \alpha + \beta_1 TREAT_i{\times}AFTER_t + \beta_2 TREAT_i + \beta_3 AFTER_t + \beta_4 Q_{i,t-1} +$$
$$\gamma_1 SPREAD_{i,t-1}\ (\text{or } \gamma_1 ZERORET_{i,t-1}) + \gamma_2 ZERORET_{i,t-1}\ (\text{or } \gamma_2 DELAY_{i,t-1})$$
$$+\gamma_3 BLOCKO_{i,t-1}\ (\text{or } \gamma_3 NBLOCK_{i,t-1}) + INDUSTRY_i + \varepsilon, \tag{28}$$

where *TREAT* is a dummy variable equal to one (zero) if a firm is in the treatment (control) group, *AFTER* is a dummy variable equal to one for 2010 (post-event year) and zero for 2008, and $Q_{i,t-1}$ denotes Tobin's Q of firm *i* in year *t-1*. Panels C and D of Table XXII report the results of estimating Equation (28). In Panel C, the coefficient of *TREAT×AFTER* is always positive and significant at the 1% level. In Column 1 with firm value (*Q*) controlled for, the coefficient of *TREAT×AFTER* is 0.150. Compared to the benchmark difference-in-differences estimator of 0.169 in Column 1 of Panel A, it represents a drop of 11.24%.[95] It suggests that the channel of firm value can explain 11.24% of the total effect of dark trading on the one-year expected default frequency. In Columns 2 to 9, the smallest coefficient of *TREAT×AFTER* is 0.139, corresponding to a drop of 17.75% compared to the benchmark of 0.169. It suggests that firm value together with the three underlying mechanisms can explain up to 17.75% of the total

[95] We have (0.150-0.169)/(0.169)=-0.1124.

effect of dark trading on the one-year expected default frequency. In Panel D, the smallest coefficient of *TREAT×AFTER* is 0.154, which represents a drop of 22.61% when compared to the benchmark difference-in-differences estimator of 0.199 in Column 1 of Panel B. It suggests that firm value together with the three underlying mechanisms can explain up to 22.61% of the total effect of dark trading on the five-year expected default frequency. Overall, it can be stated that a significant residual or direct effect for dark trading can influence default risk. Also the magnitude of the residual effect surpasses that of the indirect effect induced by the underlying mechanisms and firm value. It demonstrates a novel role of dark trading affecting firm default risk.

6.5 Concluding Remarks

Using a sample of Australian stocks during the 2005-2015 period, we examine the impact of dark trading and block trading on firm default risk, as measured by expected default frequency. We find firms with more dark trading have higher default risk, although block trading exerts little effect. A one-standard-deviation increase in the dark trading variable leads to the one-year default frequency increased by over 17% of its mean and the five-year default frequency increased by over 11% of its mean, which suggests an economically significant impact of dark trading on default risk. To address the problem of endogeneity, we adopt an instrumental variable approach and a difference-in-differences based on an exogenous event to dark trading activities, which supports a causal effect of dark trading on default risk. Based on the difference-in-differences approach, we further explore four possible mechanisms through which dark trading could affect default risk: stock liquidity, stock price informational efficiency, corporate governance by blockholders, and financial constraints.

We find that an increase in dark trading surrounding the exogenous event increases stock illiquidity and block ownership, although there is in fact little impact on informational efficiency and financial constraints. By comparing the stock liquidity channel and the corporate governance channel, we show that the stock liquidity channel has higher explanatory power for the effect of dark trading on firm default risk. In Chapter 5, we find a negative link between dark trading and firm value. Firms with higher valuation are less likely to miss their debt obligation, and therefore it is possible that the positive effect of dark trading on default risk is mechanical via decreased firm value. We demonstrate that dark trading activities increase firm default risk even after controlling for the firm value channel, and there exists a significant residual effect of dark trading on default risk even after controlling for the underlying mechanisms. It presents a novel effect of dark trading on firm default risk. The failure of a business is an event of fundamental importance in economic life, however, understanding the determinants of firm default risk is far from complete. This is particularly the case with respect to the evolution of financial markets transformed by technology. Technology has facilitated the emergence of dark pools and rapid growth in dark trading. We document that dark trading increases firm default risk, revealing an undesired impact of dark trading activities.

Chapter 7

Conclusion

Over the past two decades, trading without pre-trade transparency has grown substantially, both in the number of dark pools launched and in the market share of dark trading activities (i.e., in the relative volume of trading in dark pools). Dark pools have become an important part of the equity market structure. So far, the debate on the benefits and costs of dark trading is largely concentrated on how it influences the market quality from the perspective of market microstructure. Little is known about the overall welfare implications of dark trading from the perspective of corporate finance, as well as block trading as an old form of dark trading managed by upstairs brokers. This thesis examines the effects of dark trading and block trading on firm valuation and default risk, lying at the intersection of the literature on market microstructure and corporate finance.

Based on a sample of Australian stocks during the 2005-2015 period, this thesis finds that firms that engage in more dark trading tend to have less market valuation and more default risk, although there is little effect associated with block trading. Our results are robust to various endogeneity tests. To establish the causal effects, we adopt an instrument variable approach and a difference-in-differences approach based on exogenous shocks to dark trading. We show that the effect of dark trading on firm valuation is stronger for firms with lower stock liquidity and a detrimental impact of dark trading on stock liquidity. However, the changes in stock price informational efficiency and blockholder ownership are not significant around exogenous shocks to dark trading. It suggests dark trading harms firm valuation by reducing stock liquidity. We also explore four mechanisms through which dark trading could increase firm default risk and find that the stock liquidity channel has the highest explanatory power. We further demonstrate that the effect of dark trading on default risk is not mechanical via decreased firm value, and residual effects of dark trading exist on firm value and default risk even after controlling for the underlying mechanisms. Taken together, this thesis reveals two adverse real effects of dark trading in terms of reducing firm value and increasing default risk.

This thesis makes several contributions to the literature. First, it contributes to the growing literature that examines the impacts of dark trading and emergence of dark pools. Prior studies largely focus on the relationship of dark trading activities with characteristics of market quality, such as trading costs (O'Hara and Ye, 2011; Hatheway, Kwan, and Zheng, 2017), stock liquidity (Gresse, 2006; Weaver, 2014), adverse selection risk (Ready, 2013; Comerton-Forde, Malinova, and Park, 2018), price discovery (Comerton-Forde and Putninš, 2015). However, both theoretical models and empirical studies generate mixed conclusions on the costs and benefits of dark trading. For instance, conflicting theoretical predictions exist concerning the impacts of dark trading on price discovery. Ye (2010) predicts that dark trading harms price discovery, while Zhu (2014) predicts a positive association between dark trading and price discovery. Empirically, Foley and Putninš (2016) find dark limit order markets beneficial to market quality, but Hatheway, Kwan, and Zheng (2017) show that dark venues have a detrimental effect on market quality of lit market. Overall, the literature is still debating on whether investors should be afraid of the dark.

This thesis takes a different perspective on examining the real impacts of dark trading by focusing on its aggregate effects on firm valuation and default risk. Any benefits of dark trading on market quality could be offset or dominated by its potential costs, and, in addition, it is unclear whether changes in market quality induced by dark trading could be translated to changes in firm fundamentals. By using Australian data, this thesis documents two detrimental effects of dark trading in terms of reducing firm valuation and increasing firm default risk. There are two benefits of adopting Australian data for understanding the impacts of dark trading. On the one hand, ASX operates a single source with consolidated trading records covering all trade types of lit, dark and block trades. It enables us to distinguish different types of trades at an individual stock level and to have consistent transaction time-stamps across trading venues. On the other hand, market structure changes occur in the Australian market during our sample period, which generate exogenous variations in dark trading. We adopt them as quasi-natural experiments to address the endogeneity issues and to establish the causal effects of dark trading on firm value and default risk.

Second, this thesis contributes to the literature concerning the effects of block trading. Block trading is an old form of dark trading and managed by upstairs brokers. It existed long before the emergence of dark pools. Prior studies argue that block trading tends to be uninformed (see, e.g., Grossman, 1992; Madhavan and Cheng, 1997; Bessembinder and Venkataraman, 2004; Nimalendran and Ray, 2014). Comerton-Forde and Putninš (2015) also find little evidence of block trading affecting price discovery. Unlike dark trading that is executed directly on dark pools, upstairs brokers could facilitate block trades by tapping into unexpressed liquidity of large institutional traders, as well as credibly signaling the likely motivation for the trade. We find little effect of block trading on firm value or default risk. It supports the contention that block trading is largely uninformed and complements prior literature about the minimal impact of block trading on market quality and the corporate information environment.

Third, this thesis contributes to the emerging literature that links financial market trading characteristics to firm fundamentals, lying at the intersection of market microstructure and corporate finance literature. Starting from Brennan, Chordia, and Subrahmanyam (1998) and Datar, Naik, and Radcliffe (1998) who find that high trading activity in a firm's stock implies a lower cost of capital, prior studies have linked stock liquidity to firm valuation, innovation performance, default risk, and stock price crash risk (Fang, Noe, and Tice, 2009; Fang, Tian, and Tice, 2014; Brogaard, Li, and Xia, 2017; Chang, Chen, and Zolotoy, 2017), option trading to firm valuation and cost of equity capital (Roll, Schwartz, and Subrahmanyam, 2009; Naiker, Navissi, and Truong, 2013), trading in CDSs to firm valuation, innovation performance, and corporate debt structure (Narayanan and Uzmanoglu, 2018; Chang, Chen, Wang, Zhang, and Zhang, 2019; Chen, Saffar, Shan, and Wang, 2018), individual investor trading to firm valuation (Wang and Zhang, 2015b), and order flow volatility to equity costs of capital (Chordia, Hu, Subrahmanyam, and Tong, 2019). This thesis is the first study in the literature on this topic to examine the impacts of dark trading on firm fundamentals.

Fourth, this thesis adds to Australian studies of dark trading. He and Lepone (2014) investigate the determinants of liquidity and execution probability in the ASX's operated dark pool and find no evidence of dark trading being detrimental to market quality. Foley and Putninš (2014) examine the effectiveness of regulatory efforts to reduce dark trading and find the price improvement rule having little impact on market quality. Comerton-Forde and Putninš (2015) find low levels of dark trading benign or even benefitting information efficiency, but high levels are harmful. Foley and Putninš (2016) show that dark limit order markets are beneficial to market quality, although the effects of dark midpoint crossing systems are not consistent. This thesis focuses on the value and risk implications of dark trading in Australian market and documents two determinant effects of dark trading of economic significance.

Last but not least, the findings of this thesis provide important reference to the market structure regulators and have policy implications. Given the rapid growth of dark trading, many regulators and the world's stock exchanges have expressed concern about the detrimental effects of dark trading. However, the existing evidence is ambiguous from the perspective of market microstructure and the effects of dark trading on the real economy are unexplored. This thesis show that dark trading reduces firm valuation and increases firm default risk. It reveals two undesirable economic consequences that dark trading may bring to financial markets. Since dark trading activities can be altered by changing financial market regulations, it would help regulators to take into account the real effects of dark trading on economic fundamentals. Future research could explore other possible channels for dark trading and how they affect the real economy, and examine the role of dark trading activities in explaining the cross-sectional variation in stock returns and their short-run and long-run impacts.

• Figures

Figure I

Order Submission Route in Lit Markets

This figure illustrates the order submission route in lit markets. Clients submit orders to brokers for execution. Brokers send the orders to the exchange market for them to be executed. Such orders are subject to arbitrage strategies from high frequency traders as their details are revealed to the public on the exchange.

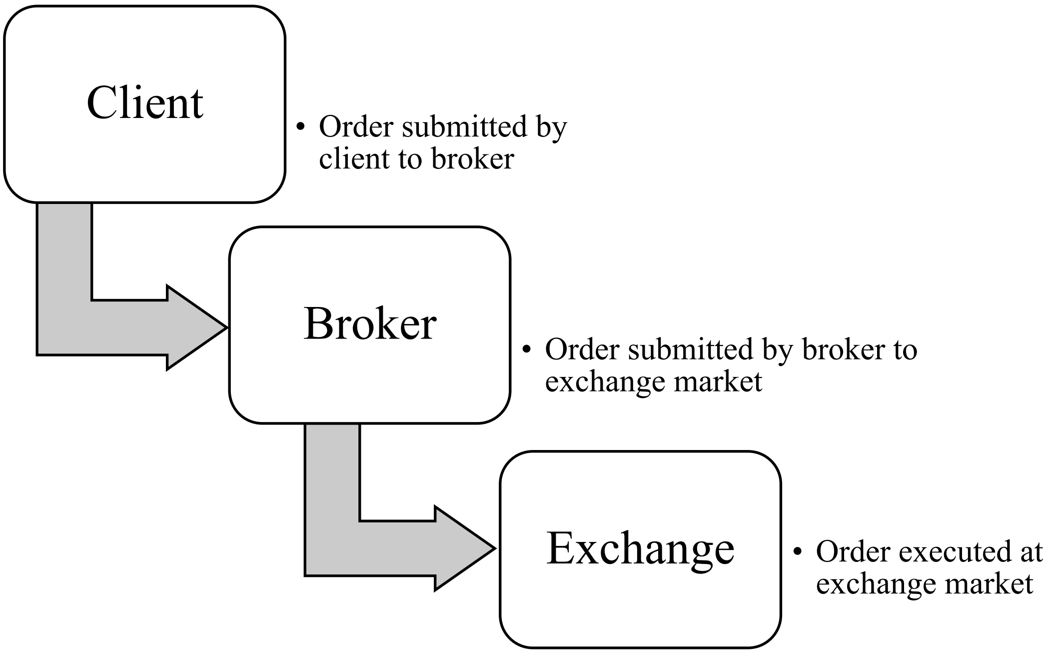


Figure II

Order Submission Route in Dark Pools

This figure illustrates the order submission route in dark pools. Clients submit orders to brokers for execution. Instead of sending orders to the exchange, brokers can first try to match orders in their own dark pools with the orders of other clients and their own. In case they cannot fill in the orders in their own dark pools, brokers may send orders to the exchange for execution directly. Alternatively, brokers may search outside dark pools that are operated by other brokers for execution, and unfilled orders will be sent to the exchange eventually.

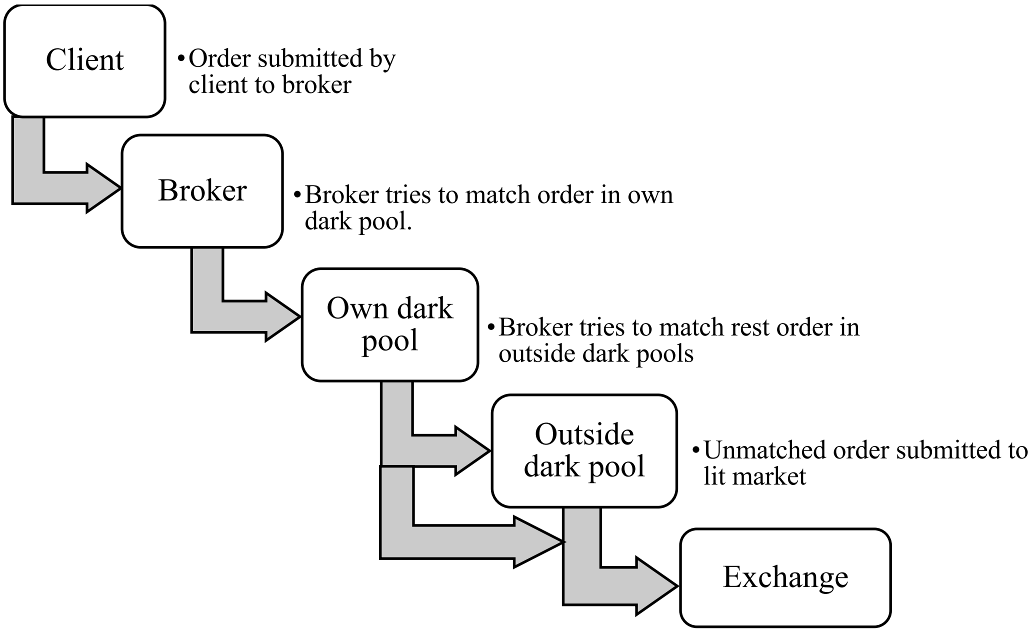
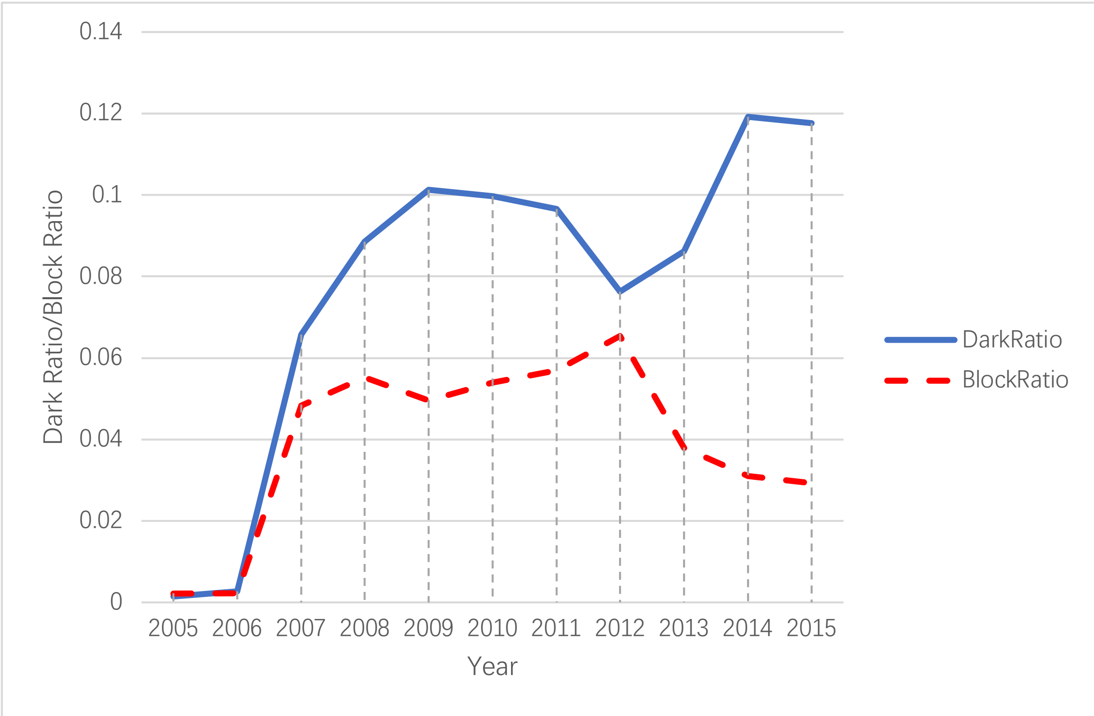


Figure III

Dark Trading Ratio and Block Trading Ratio over the Sample Period from 2005 to 2015

This figure shows the yearly average dark trading ratio (*DarkRatio*) and block trading ratio (*BlockRatio*) over our sample period from 2005 to 2015. The definitions of *DarkRatio* and *BlockRatio* are provided in Table I.



• **Appendix**

Appendix I

Operating Dark Venues in Australia

The table below shows details of operating dark venues and number of operators in Australia for each year. Panel A presents details of operating dark venues including operator, identifier and date of commencement (and ceased date). Panel B provides the numbers of venues in each year. We calculate the number of dark venues in each year by using the number of operating venues minus the number of ceased operations.

Panel A: Details of Operating Dark Venues in Australia

Operator of crossing system	Crossing system identifier	Date of commencement
BestEx Pty Ltd		March-2015 (ceased operation June-2015)
BestEx Pty Ltd - Block Event	2011	26-Nov-2015
Citigroup Global Markets Australia		
- Crossing System 2	2032	Jul-2013
- Crossing System 1		February-2006 (ceased operation July-2014)
CLSA Australia Pty Ltd	2311	Oct-2012
Commonwealth Securities Limited		
- Crossing System 3		November-2012 (ceased operation April-2014)
- Crossing System 2		2011/5/1 (ceased operation October-2013)
- Crossing System 1		May-2011 (ceased operation February-2014)
Credit Suisse Equities (Australia) Limited		
- Crossing System 2		May-2009 (ceased operation October-2016)
- Crossing System 1	1101	Apr-2006
Deutsche Securities Australia Limited		
- Crossing System 2	2102	Jun-2011
- Crossing System 1		June-2010 (ceased operation May-2013)
*E*TRADE*		February-2013 (ceased operation May-2013)
Goldman Sachs Australia Pty Ltd	3611	Jan-2010
ICAP Futures (Australia) Pty Limited		
- Crossing System 2	CAP 2	Aug-2017
- Crossing System 1	CAP 1	Sep-2015
Instinet Australia Pty Limited	2171	Apr-2011
ITG Australia Limited	3451	May-2010
J.P. Morgan Securities Limited		
- Crossing System 2	2972	Oct-2015

- Crossing System 1		August-2011 (ceased operation June-2016)
Liquidnet Australia Pty Ltd	9991	Feb-2008
Macquarie Securities (Australia) Limited		
- Crossing System 2	1562	Mar-2018
- Crossing System 1	1561	Sep-2010
Merrill Lynch Equities (Australia) Limited	3661	August-2010 (ceased operation 6-March-2017)
Morgan Stanley Australia Securities Limited	2991	Mar-2010
State One Stockbroking Ltd	6781	Nov-2012
UBS		
Securities Australia Ltd		
- Crossing System 2		August-2012 (ceased operation January-2016)
- Crossing System 1	1501	Aug-2005

Panel B: Number of Dark Venues in Each Year

Year	**Number of operators**
2005	1
2006	3
2007	3
2008	4
2009	5
2010	11
2011	16
2012	20
2013	19
2014	16
2015	19

Appendix II

Details of Industry Classifications

Our first industry set is first 2-digit GICS code. There are 24 industries in original 4-digit GICS code including energy (code number 1010), materials (code number 1510), capital goods (code number 2010), commercial and professional services (code number 2020), transportation (code number 2030), automobiles and components (code number 2510), consumer durables and apparel (code number 2520), consumer services (code number 2530), media (code number 2540), retailing (code number 2550), food and staples retailing (code number 3010), food, beverage and tobacco (code number 3020), household and personal products (code number 3030), health care equipment and services (code number 3510), pharmaceuticals, biotechnology & life sciences (code number 3520), banks (code number 4010), diversified financials (code number 4020), insurance (code number 4030), software and services (code number 4510), technology hardware and equipment (code number 4520), semiconductors and semiconductor equipment (code number 4530), telecommunication services (code number 5010), utilities (code number 5510), and real estate (code number 6010). When considering the first 2 digits of the 4-digit GICS code, there are 11 industries in our first industry set (2-digit code number 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60). There are 6 industries in our second industry set including industrial (code number 1), utility (code number 2), transportation (code number 3), banking (code number 4), insurance (code number 5) and other financial company (code number 6).

Appendix III

Variance Inflation Factors of the independent variables

Panels A and B below report the Variance Inflation Factors (VIF) of independent variables in estimating the baseline specification for the study of firm valuation and for the study of firm default risk, respectively. We use R_i^2 to represent the proportion of variance in the *i*th independent variable that is associated with the other independent variables in the model. Then the VIF is calculating by using $1/(1-R_i^2)$. A VIF of 5 and above indicates a multicollinearity problem (O'Brien, 2007). As shown in Panel A (B), the VIFs of the independent variables are all below 2.7 (2.4) and consequently our analysis is not subject to the multicollinearity problem.

Panel A: VIF of the Independent Variables in the Study of Firm Valuation	
Variables	Variance Inflation Factors (VIF)
$DARK_{t-1}$	1.800
$BLOCK_{t-1}$	1.844
$SIZE_{t-1}$	2.683
$TURNOVER_{t-1}$	1.080
IO_{t-1}	1.401
$ANALYST_{t-1}$	2.291
LTD_{t-1}	1.111
$CAPX_{t-1}$	1.156
$IDIO_{t-1}$	2.450
$DIVD_{t-1}$	1.930
ROA_{t-1}	1.119
Panel B: VIF of the Independent Variables in the Study of Firm Default Risk	
Variables	Variance Inflation Factors (VIF)
$DARK_{t-1}$	2.314
$BLOCK_{t-1}$	2.344
Ln(EQUITY)	1.809
Ln(DEBT)	1.252
$1/\sigma_E$	1.662
EX_RET	1.001
ROA	1.006

• **Tables**

Table I
Definitions of Variables and Summary Statistics in the Study of Firm Valuation

Panel A of this table provides the definitions of variables used in the study of the impacts of dark trading and block trading on firm valuation. Panel B reports descriptive statistics of the variables. There are 3,687 firm-year observations over the sample period from 2005 to 2015.

Panel A: Variable Definitions

Variables	Definitions
Q	Tobin's Q ratio, calculated by using market value of assets divided by book value of total assets, where the market value of assets equals to market value of equity plus book value of assets mines book value of equity mines balance sheet deferred taxes.
DarkRatio	Dark trading ratio, calculated as the average of daily dark trading ratio that is the dollar volume of dark trades as a percentage of the total dollar volume in the stock-day.
DARK	Natural logarithm of dark trading ratio.
BlockRatio	Block trading ratio, calculated as the average of daily block trading ratio that is the dollar volume of block trades as a percentage of the total dollar volume in the stock-day.
BLOCK	Natural logarithm of block trading ratio.
SIZE	Natural logarithm of market capitalization.
TURNOVER	Share turnover, measured by the average number of shares traded as a percentage of the total number of shares outstanding.
IO	Institutional ownership, measured as the proportion of shares held by institutional investors to the total number of shares outstanding.
ANALYST	Analyst coverage, calculated as the natural logarithm of one plus the number of analysts who issue at least one earnings forecast during the firm's fiscal year.
LTD	Long-term debt of the firm, calculated by using long-term debt divided by book value of assets.
CAPX	Capital expenditures of the firm, calculated by using capital expenditures divided by sales.
IDIO	Idiosyncratic risk of the firm, measured by the standard deviation of the residuals from estimating the market model.
DIVD	Dummy variable of dividend payout, equals one if firm pays dividend and zero otherwise.
ROA	Return on assets measured by net income divided by book value of assets.

Panel B: Summary Statistics

Variables	Mean	Std. dev.	25%	Median	75%
Q	1.884	2.107	0.919	1.250	2.059
DarkRatio	0.075	0.052	0.045	0.069	0.105
DARK	-3.152	1.575	-3.085	-2.664	-2.245
BlockRatio	0.040	0.049	0.000	0.021	0.063
BLOCK	-4.468	1.944	-6.908	-3.816	-2.754
SIZE	19.431	1.808	18.140	19.219	20.680
TURNOVER	0.008	0.036	0.001	0.002	0.004
IO	0.081	0.085	0.015	0.053	0.120
ANALYST	1.306	0.941	0.693	1.386	2.197
LTD	0.156	0.192	0.000	0.088	0.260
CAPX	0.095	0.132	0.012	0.044	0.120
IDIO	0.031	0.018	0.018	0.031	0.040
DIVD	0.577	0.494	0.000	1.000	1.000
ROA	-0.081	0.926	-0.057	0.031	0.083

Table II
Correlation Matrix of Independent Variables in the Study of Firm Valuation

This table reports the Pearson correlation between independent variables used in the baseline regression specification for the study of the impacts of dark trading and block trading on firm valuation. The definitions of the variables are provided in Table I. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	DARK	*BLOCK*	*SIZE*	*TURNOVER*	*IO*	*ANALYST*	*LTD*	*CAPX*	*IDIO*	*DIVD*
DARK	1									
BLOCK	0.588***	1								
SIZE	0.008	0.227***	1							
TURNOVER	0.030*	0.011	-0.129***	1						
IO	0.049***	0.167***	0.512***	-0.054***	1					
ANALYST	0.056***	0.290***	0.704***	-0.122***	0.411***	1				
LTD	-0.137***	-0.007	0.255***	-0.049***	0.129***	0.240***	1			
CAPX	-0.051***	-0.054***	-0.128***	0.084***	0.016	-0.165***	-0.022	1		
IDIO	0.220***	-0.010	-0.618***	0.241***	-0.263***	-0.541***	-0.251***	0.223***	1	
DIVD	-0.129***	0.067***	0.467***	-0.163***	0.165***	0.502***	0.241***	-0.330***	-0.646***	1
ROA	-0.075***	0.035**	0.215***	-0.155***	0.086***	0.178***	0.061***	-0.108***	-0.312***	0.263***

Table III

Definitions of Variables and Summary Statistics in the Study of Firm Default Risk

Panel A of this table provides the definitions of variables used in the study of the impacts of dark trading and block trading on firm default risk. Panel B reports descriptive statistics of the variables. There are 6,049 firm-year observations over the sample period from 2005 to 2015.

Panel A: Variable Definitions

Variables	Definitions
DD_1y	One-year distance-to-default, calculated following Bharath and Shumway (2008).
DD_5y	Five-year distance-to-default, calculated following Bharath and Shumway (2008).
EDF_1y	One-year expected default frequency, computed as N(-*DD_1y*), where N(.) is the cumulative standard normal distribution function.
EDF_5y	Five-year expected default frequency, computed as N(-*DD_5y*), where N(.) is the cumulative standard normal distribution function.
DarkRatio	Dark trading ratio, calculated as the average of daily dark trading ratio that is the dollar volume of dark trades as a percentage of the total dollar volume in the stock-day.
DARK	Natural logarithm of dark trading ratio.
BlockRatio	Block trading ratio, calculated as the average of daily block trading ratio that is the dollar volume of block trades as a percentage of the total dollar volume in the stock-day.
BLOCK	Natural logarithm of block trading ratio.
EQUITY	Market value of equity (in billions of Australian dollars).
DEBT	Face value of debt (in billions of Australian dollars).
σ_E	Annualized stock return volatility calculated based on daily returns.
EX_RET	Annual excess return, calculated as the difference between the stock's annual return and the All Ordinaries index annual return.
ROA	Return of assets calculated as net income divided by book value of assets.

Panel B: Summary Statistics

Variables	Mean	Std. dev.	25%	Median	75%
DD_1y	14.363	21.284	2.974	6.853	16.832
DD_5y	7.546	23.128	0.107	3.901	9.425
EDF_1y	0.085	0.227	0.000	0.000	0.001
EDF_5y	0.248	0.388	0.000	0.000	0.457
DarkRatio	0.088	0.097	0.044	0.074	0.112
DARK	-5.546	7.341	-3.112	-2.604	-2.194
BlockRatio	0.034	0.047	0.000	0.014	0.052
BLOCK	-10.630	9.482	-23.026	-4.262	-2.966
EQUITY	1.454	6.059	0.049	0.153	0.616
DEBT	0.691	3.599	0.000	0.017	0.147
σ_E	0.640	0.648	0.324	0.492	0.756
EX_RET	1.315	18.033	-0.277	0.013	0.407
ROA	-0.070	0.364	-0.084	0.023	0.074

Table IV
Correlation Matrix of Independent Variables in the Study of Firm Default Risk

This table reports the Pearson correlation between independent variables used in the baseline regression specification for the study of the impacts of dark trading and block trading on firm default risk. The definitions of the variables are provided in Table III. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	DARK	*BLOCK*	*Ln(EQUITY)*	*Ln(DEBT)*	$1/\sigma_E$	*EX_RET*	*ROA*
DARK	1						
BLOCK	0.714***	1					
Ln(EQUITY)	0.073***	0.135***	1				
Ln(DEBT)	0.010	0.031**	0.427***	1			
$1/\sigma_E$	-0.192***	-0.143***	0.574***	0.324***	1		
EX_RET	0.031**	-0.002	-0.128***	-0.082***	-0.178***	1	
ROA	-0.062***	0.018	0.355***	0.195***	0.329***	-0.113***	1

Table V

Effects of Dark and Block Trading Activities on Firm Valuation

This table reports the regression results for examining the effects of dark trading and block trading on firm valuation. The dependent variable is Tobin's Q (*Q*), calculated by using market value of assets divided by book value of total assets. *DARK* (*BLOCK*) denotes the natural logarithm of dark (block) trading ratio that is the dollar volume of dark (block) trades as a percentage of the total dollar volume. All independent variables are lagged by 1 year. Definitions of the variables are provided in Table I. Industry fixed effects are constructed based on either 2-digit GICS code (Industry1) or General Industry Classification (Industry2). In Columns 3 and 6, both industry and year fixed effects are included. Panels A and B examine the effects of *DARK* and *BLOCK* on firm valuation, respectively, while Panel C includes both *DARK* and *BLOCK* as independent variables. t-statistics calculated based on heteroskedasticity-consistent standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Effect of Dark Trading on Firm Valuation

	Q				
	(1)	(2)	(3)	(4)	(5)
DARK	-0.178***	-0.164***	-0.207***	-0.184***	-0.132*
	(-9.571)	(-7.488)	(-2.789)	(-8.225)	(-1.793)
SIZE	0.267***	0.371***	0.372***	0.310***	0.307***
	(8.581)	(9.977)	(10.051)	(9.008)	(9.019)
TURNOVER	-0.167	0.463	0.210	-0.150	-0.360
	(-0.229)	(0.354)	(0.160)	(-0.110)	(-0.262)
IO	-1.817***	-1.705***	-1.687***	-2.033***	-1.943***
	(-4.005)	(-4.228)	(-4.180)	(-5.054)	(-4.852)
ANALYST	-0.025	-0.142***	-0.126***	-0.027	0.006
	(-0.478)	(-2.980)	(-2.646)	(-0.570)	(0.119)
LTD	-1.394***	-1.165***	-1.221***	-1.488***	-1.575***
	(-7.778)	(-5.532)	(-5.696)	(-6.595)	(-6.849)
CAPX	-0.080	0.937*	0.917*	-0.224	-0.280
	(-0.309)	(1.871)	(1.853)	(-0.473)	(-0.597)
IDIO	18.763***	21.795***	25.336***	18.293***	20.353***
	(5.901)	(5.352)	(5.010)	(4.526)	(4.039)
DIVD	-0.151	-0.213*	-0.160	-0.153	-0.125
	(-1.624)	(-1.842)	(-1.343)	(-1.308)	(-1.036)
ROA	-1.106***	-1.088***	-1.097***	-1.133***	-1.139***
	(-15.893)	(-4.736)	(-4.792)	(-4.676)	(-4.721)
Fixed effects	None	Industry1	Industry1, Year	Industry2	Industry2, Year
No. of obs.	3,687	3,687	3,687	3,687	3,687
R^2	12.32%	18.15%	19.62%	13.49%	15.01%
Adjusted R^2	12.08%	17.70%	18.96%	13.14%	14.43%

Table V - *Continued*

Panel B: Effect of Block Trading on Firm Valuation					
	Q				
	(1)	(2)	(3)	(4)	(5)
BLOCK	-0.116***	-0.097***	-0.019	-0.124***	-0.064
	(-6.327)	(-5.449)	(-0.393)	(-6.712)	(-1.333)
SIZE	0.261***	0.363***	0.373***	0.304***	0.310***
	(8.325)	(9.719)	(10.057)	(8.812)	(9.078)
TURNOVER	0.019	0.658	0.179	0.047	-0.336
	(0.026)	(0.504)	(0.136)	(0.035)	(-0.244)
IO	-1.846***	-1.784***	-1.574***	-2.085***	-1.845***
	(-4.039)	(-4.351)	(-3.902)	(-5.093)	(-4.633)
ANALYST	-0.016	-0.139***	-0.098*	-0.014	0.042
	(-0.302)	(-2.772)	(-1.924)	(-0.278)	(0.828)
LTD	-1.273***	-1.027***	-1.223***	-1.342***	-1.562***
	(-7.084)	(-4.860)	(-5.719)	(-5.981)	(-6.835)
CAPX	0.102	1.096**	0.913*	-0.042	-0.282
	(0.397)	(2.217)	(1.847)	(-0.091)	(-0.603)
IDIO	15.202***	18.014***	24.292***	14.714***	19.402***
	(4.803)	(4.448)	(4.824)	(3.653)	(3.865)
DIVD	-0.128	-0.181	-0.171	-0.128	-0.130
	(-1.372)	(-1.578)	(-1.433)	(-1.103)	(-1.073)
ROA	-1.109***	-1.074***	-1.089***	-1.117***	-1.133***
	(-15.581)	(-4.708)	(-4.775)	(-4.663)	(-4.718)
Fixed effects	None	Industry1	Industry1, Year	Industry2	Industry2, Year
No. of obs.	3,687	3,687	3,687	3,687	3,687
R^2	11.10%	16.97%	19.42%	12.27%	14.98%
Adjusted R^2	10.86%	16.52%	18.76%	11.91%	14.40%

Table V - *Continued*

Panel C: Effects of Dark Trading and Block Trading on Firm Valuation					
	Q				
	(1)	(2)	(3)	(4)	(5)
DARK	-0.168***	-0.165***	-0.209***	-0.169***	-0.138*
	(-7.178)	(-6.338)	(-2.845)	(-6.379)	(-1.894)
BLOCK	-0.016	0.000	-0.025	-0.023	-0.069
	(-0.707)	(0.008)	(-0.535)	(-1.111)	(-1.439)
SIZE	0.269***	0.371***	0.373***	0.312***	0.309***
	(8.608)	(9.985)	(10.078)	(9.082)	(9.083)
TURNOVER	-0.155	0.463	0.226	-0.132	-0.303
	(-0.212)	(0.353)	(0.172)	(-0.097)	(-0.219)
IO	-1.813***	-1.705***	-1.674***	-2.030***	-1.920***
	(-3.994)	(-4.227)	(-4.124)	(-5.042)	(-4.792)
ANALYST	-0.018	-0.142***	-0.117**	-0.017	0.031
	(-0.338)	(-2.905)	(-2.238)	(-0.340)	(0.581)
LTD	-1.394***	-1.165***	-1.220***	-1.487***	-1.565***
	(-7.777)	(-5.517)	(-5.694)	(-6.588)	(-6.825)
CAPX	-0.076	0.937*	0.916*	-0.219	-0.281
	(-0.295)	(1.869)	(1.854)	(-0.463)	(-0.603)
IDIO	18.901***	21.794***	25.225***	18.486***	19.993***
	(5.933)	(5.315)	(5.001)	(4.548)	(3.971)
DIVD	-0.150	-0.213*	-0.159	-0.152	-0.123
	(-1.616)	(-1.840)	(-1.338)	(-1.300)	(-1.011)
ROA	-1.104***	-1.088***	-1.096***	-1.131***	-1.138***
	(-15.866)	(-4.745)	(-4.801)	(-4.683)	(-4.732)
Fixed effects	None	Industry1	Industry1, Year	Industry2	Industry2, Year
No. of obs.	3,687	3,687	3,687	3,687	3,687
R^2	12.33%	13.52%	15.07%	13.52%	15.07%
Adjusted R^2	12.07%	13.14%	14.47%	13.14%	14.47%

Table VI

Endogeneity Test in the Study of Firm Valuation: Firm Fixed Effects

This table uses firm fixed effects as an endogeneity control following Fang, Noe, and Tice (2009) in the study of examining the effects of dark trading and block trading on firm valuation. Except dummy variable *DIVD*, we apply industry adjustment to all of the dependent, independent, and control variables by subtracting the median value of the firm's industry that is classified based on 2-digit GICS codes. Tobin's Q (*Q*) is calculated by using market value of assets divided by book value of total assets. *Adjust_Q* is the industry-adjusted variable of firm valuation. *Adjust_DARK* (*Adjust_BLOCK*) denotes the industry-adjusted variable of dark (block) trading, while industry-adjusted variables of other independent variables are denoted similarly. Definitions of the variables are provided in Table I. In Columns 4 and 6, year fixed effects are included in addition to firm fixed effects. t-statistics calculated based on heteroskedasticity-consistent standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Adjust_Q					
	(1)	(2)	(3)	(4)	(5)	(6)
Adjust_DARK	-0.177***		-0.179***	-0.145**		-0.142*
	(-9.758)		(-8.074)	(-2.210)		(-1.767)
Adjust_BLOCK		-0.088***	0.002		-0.108***	-0.107
		(-5.420)	(0.108)		(-2.674)	(-1.631)
Adjust_SIZE	0.218***	0.143***	0.217***	0.194***	0.205***	0.198*
	(4.387)	(2.899)	(4.372)	(3.839)	(4.066)	(1.676)
Adjust_TURNOVER	-3.941***	-3.584***	-3.945***	-4.511***	-4.329***	-4.328
	(-3.621)	(-3.260)	(-3.622)	(-4.163)	(-3.988)	(-1.497)
Adjust_IO	-1.721***	-2.287***	-1.719***	-1.486**	-1.406**	-1.443
	(-2.924)	(-3.871)	(-2.919)	(-2.528)	(-2.393)	(-1.244)
Adjust_ANALYST	-0.099	-0.145**	-0.099	-0.050	-0.007	-0.019
	(-1.550)	(-2.251)	(-1.552)	(-0.77)	(-0.112)	(-0.200)
Adjust_LTD	-0.735***	-0.647***	-0.734***	-0.898***	-0.937***	-0.933***
	(-3.123)	(-2.720)	(-3.114)	(-3.798)	(-3.959)	(-2.679)
Adjust_CAPX	0.953***	1.268***	0.952***	0.887***	0.885***	0.884
	(3.289)	(4.371)	(3.286)	(3.073)	(3.068)	(1.086)
Adjust_IDIO	15.455***	9.383***	15.444***	18.629***	17.027***	17.608***
	(5.004)	(3.097)	(4.998)	(4.946)	(4.510)	(2.621)
DIVD	0.069	0.163	0.069	0.094	0.102	0.103
	(0.613)	(1.433)	(0.608)	(0.84)	(0.905)	(0.758)
Adjust_ROA	-0.405***	-0.366***	-0.405***	-0.429***	-0.439***	-0.433*
	(-5.740)	(-5.146)	(-5.739)	(-6.131)	(-6.285)	(-1.705)
Fixed effects	Firm	Firm	Firm	Firm, Year	Firm, Year	Firm, Year
No. of obs.	3,687	3,687	3,687	3,687	3,687	3,687
R^2	60.99%	60.14%	60.99%	62.15%	62.18%	62.24%
Adjusted R^2	51.90%	50.85%	51.88%	53.16%	53.20%	53.26%

Table VII

Endogeneity Test in the Study of Firm Valuation: Two-Stage Least Squares (2SLS)

This table reports the 2SLS regression results for the effects of dark trading and block trading on firm valuation. In the first-stage regressions, *DARK* and *BLOCK* are regressed on two instrumental variables and control variables. Following Comerton-Forde and Putninš (2015), we construct instrumental variables based on market structure changes that are exogenous with respect to firm valuation but influence the amount of dark and block trading. The market structure changes include: (i) the removal of the ten-second rule on November 30, 2009 which makes it easier to execute dark trades; and (ii) the change in ASX trading fees on July 1, 2010 which changes the relative explicit costs of trading in the dark compared to trading in the CLOB. We construct a dummy variable $D^{rule\ remove}$ ($D^{fee\ reduce}$) that equals to 1 if the end of the fiscal year is after November 30, 2009 (July 1, 2010) and zero before. Definitions of the other variables are provided in Table I. All the variables are one year lagged and Panel A reports the results of the first-stage regressions. In the second-stage regressions, Tobin's Q (*Q*) is regressed on the fitted value of dark trading (*PRE_DARK*) and the fitted value of block trading (*PRE_BLOCK*) as well as all the lagged control variables. Panel B reports the results of the second-stage regressions. *PRE_DARK* and *PRE_BLOCK* in Column 1 (2) of Panel B are the fitted values from the first-stage regressions in Columns 1.1 and 1.2 (2.1 and 2.2) of Panel A. Industry fixed effects are constructed based on either 2-digit GICS code (Industry1) or General Industry Classification (Industry2). t-statistics calculated based on heteroskedasticity-consistent standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: First-Stage Regressions

	DARK	*BLOCK*	*DARK*	*BLOCK*
	(1.1)	(1.2)	(2.1)	(2.2)
$D^{rule\ remove}$	3.088***	2.571***	3.089***	2.572***
	(48.497)	(27.071)	(48.484)	(27.091)
$D^{fee\ reduce}$	0.157***	-0.615***	0.152**	-0.608***
	(2.647)	(-6.943)	(2.555)	(-6.883)
SIZE	0.081***	0.140***	0.076***	0.136***
	(4.760)	(5.478)	(4.599)	(5.577)
TURNOVER	0.265	1.276**	0.339	1.468***
	(0.695)	(2.240)	(0.893)	(2.597)
IO	-0.534**	0.254	-0.669***	0.048
	(-2.208)	(0.703)	(-2.832)	(0.136)
ANALYST	-0.093***	0.369***	-0.082***	0.383***
	(-3.315)	(8.863)	(-3.029)	(9.479)
LTD	-0.263***	-0.300**	-0.243**	-0.097
	(-2.601)	(-1.989)	(-2.529)	(-0.680)
CAPX	-0.247*	0.080	-0.367***	0.016
	(-1.721)	(0.376)	(-2.784)	(0.083)
IDIO	8.406***	9.462***	7.742***	8.551***
	(5.104)	(3.853)	(4.773)	(3.538)
DIVD	-0.083	-0.007	-0.043	0.046
	(-1.627)	(-0.095)	(-0.895)	(0.642)
ROA	-0.036***	0.105**	-0.040	0.097*
	(-1.035)	(2.044)	(-1.164)	(1.898)
Fixed effects	Industry1	Industry1	Industry2	Industry2
No. of obs.	3,687	3,687	3,687	3,687
R^2	68.36%	35.63%	68.30%	35.60%
Adjusted R^2	68.19%	35.27%	68.17%	35.34%
F-statistic	396.5	101.5	519.5	133.3
F-test (p-value)	0.000	0.000	0.000	0.000

Table VII - *Continued*

Panel B: Second-Stage Regressions		
	Q	
	(1)	(2)
PRE_DARK	-0.076*	-0.145***
	(-1.692)	(-3.101)
PRE_BLOCK	0.081	0.146**
	(1.260)	(2.231)
SIZE	0.339***	0.277***
	(9.104)	(7.990)
TURNOVER	0.622	-0.018
	(0.473)	(-0.013)
IO	-1.884***	-2.204***
	(-4.564)	(-5.375)
ANALYST	-0.205***	-0.107**
	(-3.975)	(-2.141)
LTD	-0.932***	-1.250***
	(-4.505)	(-5.709)
CAPX	1.177**	0.125
	(2.353)	(0.267)
IDIO	14.335***	10.405***
	(3.659)	(2.644)
DIVD	-0.170	-0.124
	(-1.471)	(-1.070)
ROA	-1.092***	-1.134***
	(-4.757)	(-4.704)
Fixed effects	Industry1	Industry2
No. of obs.	3,631	3,631
R^2	16.50%	11.62%
Adjusted R^2	16.02%	11.23%

Table VIII

Endogeneity Test in the Study of Firm Valuation: Change Around Exogenous Shock in Dark Trading

This table shows changes of the impacts of dark trading on firm valuation surrounding the year of 2009 when the removal of the ten-second rule occurs. The rule removal makes it easier to execute dark trades and is adopted as an exogenous shock to dark trading activities. The sample covers one year before 2009 (year 2008) and one year after 2009 (year 2010). We rely on firms for which data are available for both the fiscal year before and the fiscal year after 2009. We construct a post-shock dummy variable (*POST*) that equals to 1 for the fiscal year after the event, and 0 for the fiscal year before the event. Firm valuation (*Q*) is regressed on the dummy variable *POST* and all the control variables. In Columns 3 and 4, variable of block trading (*BLOCK*) is further included as a control. Industry fixed effects are constructed based on either 2-digit GICS code (Industry1) or General Industry Classification (Industry2). t-statistics calculated based on heteroskedasticity-consistent standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Q			
	(1)	(2)	(3)	(4)
POST	-0.293**	-0.400***	-0.293**	-0.400***
	(-2.165)	(-2.843)	(-2.160)	(-2.842)
BLOCK			0.028	-0.039
			(0.273)	(-0.369)
SIZE	0.750***	0.582***	0.749***	0.584***
	(6.816)	(6.068)	(6.849)	(6.091)
TURNOVER	-1.354	-2.111	-1.366	-2.077
	(-0.821)	(-1.481)	(-0.816)	(-1.446)
IO	-2.962***	-3.019***	-2.977***	-3.006***
	(-3.091)	(-3.010)	(-3.117)	(-3.010)
ANALYST	-0.404***	-0.232*	-0.417***	-0.214
	(-3.367)	(-1.901)	(-3.038)	(-1.572)
LTD	-1.528***	-1.735***	-1.532***	-1.719***
	(-3.000)	(-3.515)	(-2.993)	(-3.446)
CAPX	2.160*	0.434	2.169*	0.425
	(1.894)	(0.416)	(1.878)	(0.402)
IDIO	27.226***	14.612*	27.426***	14.314*
	(3.073)	(1.748)	(3.013)	(1.673)
DIVD	-0.654***	-0.510**	-0.654***	-0.507**
	(-3.122)	(-2.440)	(-3.122)	(-2.438)
ROA	-0.141	-0.295	-0.149	-0.285
	(-0.346)	(-0.708)	(-0.369)	(-0.694)
Fixed effects	Industry1	Industry2	Industry1	Industry2
No. of obs.	612	612	612	612
R^2	26.11%	18.82%	26.12%	18.85%
Adjusted R^2	23.59%	16.76%	23.47%	16.65%

Table IX

Endogeneity Test in the Study of Firm Valuation: Difference-in-Differences Test

This table shows the difference-in-differences test of the effects of dark trading on firm valuation surrounding the year of 2009 when the removal of the ten-second rule occurs. The rule removal makes it easier to execute dark trades and is adopted as an exogenous shock to dark trading activities. We rank all sample firms based on their changes in dark trades surrounding the rule removal, and select the top 30% of the firms as treatment group and the bottom 30% of the firms as control group. We then run a probit model with the dependent variable being a dummy variable that is set to one for the firm in the treatment group and 0 in the control group. The independent variables include dark trading (*DARK*), block trading (*BLOCK*), and all the control variables used in baseline specification, and they are measured prior to the rule removal in year 2008. Definitions of the variables are provided in Table I. Propensity scores are used as predicted probabilities to match firms in two groups by closest propensity score match. Column 1 in Panel A reports regressions of estimating the probit model before match, while Column 2 reports the probit regression results after matching treatment group with control group. z-statistics are reported in parentheses. Panel B reports the statistical distributions of the propensity scores in treatment group, control group, and the differences between two groups in the matched sample. Panel C reports the average variables in treatment group, control group, and the differences in the averages of every variables in the year before event year (i.e., in year 2008). Panel D reports the average variables in treatment group, control group, and the differences in the averages of every variables in the year after event year (i.e., in year 2010). The corresponding t-statistics and p-values of the differences are also reported in Panels C and D. Panel E reports the difference-in-differences estimator of firm valuation (*Q*) based on the matched sample. Panel F reports the regression of difference-in-differences of firm valuation (*Q*) based on the matched sample. *TREAT* is a dummy variable equal to one if a stock is in the treatment group and zero if in the control group. *AFTER* is a dummy variable equal to one for 2010 (post-event year) and zero for 2008 (pre-event year). *TREAT×AFTER* is the interaction between these two variables. Industry fixed effects are constructed based on either 2-digit GICS code (Industry1) or General Industry Classification (Industry2). t-statistics calculated based on heteroskedasticity-consistent standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Probit Regressions with Pre- and Post-Matched Samples

	Before match	After match
	(1)	(2)
DARK	-3.835***	-0.771
	(-5.683)	(-1.294)
BLOCK	-0.381	-0.443**
	(-1.615)	(-1.976)
SIZE	-0.777***	-0.083
	(-4.321)	(-0.497)
TURNOVER	-3.886	8.933
	(-0.909)	(0.766)
IO	-1.422	2.401
	(-0.471)	(0.823)
ANALYST	-0.280	0.026
	(-0.780)	(0.084)
LTD	0.812	1.366
	(0.882)	(1.648)
CAPX	2.177	1.464
	(1.546)	(1.237)
IDIO	-20.567	-9.586
	(-1.033)	(-0.562)
DIVD	0.518	0.707
	(0.846)	(1.428)
ROA	-0.967	-0.400
	(-1.278)	(-0.756)
Fixed effects	None	None
No. of obs.	184	184
P-value of X^2	0.0000	0.1060
Pseudo R^2	27.54%	6.69%
Log likelihood	-92.419	-119.008

Table IX - *Continued*

Panel B: Propensity Scores Distribution						
Group	N	Mean	Minimum	Median	Maximum	SD
Treatment	92	0.664	0.095	0.666	0.950	0.218
Control	92	0.651	0.097	0.659	0.870	0.205
Difference	92	0.013	-0.002	0.007	0.080	0.014

Panel C: Differences in Variables in Pre-Event Year					
	Treatment	Control	Difference	t-statistic	p-value
DARK	-2.736	-2.670	-0.066	-1.369	0.174
BLOCK	-3.266	-3.207	-0.059	-0.413	0.681
SIZE	18.930	18.595	0.335	1.621	0.109
TURNOVER	0.011	0.005	0.006	1.319	0.191
IO	0.068	0.055	0.013	1.618	0.109
ANALYST	1.060	0.816	0.244	1.853	0.067
LTD	0.168	0.106	0.062	1.929	0.057
CAPX	0.134	0.100	0.034	1.662	0.100
IDIO	0.037	0.039	-0.002	-1.093	0.277
DIVD	0.500	0.370	0.130	1.790	0.077
ROA	-0.108	-0.069	-0.039	-0.617	0.539

Panel D: Differences in Variables in Post-Event Year					
	Treatment	Control	Difference	t-statistic	p-value
DARK	-2.253	-2.836	0.583	11.392	0.000
BLOCK	-3.505	-2.815	-0.690	-6.279	0.000
SIZE	18.660	19.360	-0.700	-3.848	0.000
TURNOVER	0.014	0.005	0.009	1.147	0.255
IO	0.061	0.093	-0.032	-2.973	0.004
ANALYST	1.021	1.285	-0.264	-2.197	0.031
LTD	0.154	0.105	0.049	1.632	0.106
CAPX	0.079	0.160	-0.081	4.542	0.000
IDIO	0.036	0.034	0.003	1.416	0.160
DIVD	0.391	0.402	-0.011	-0.168	0.867
ROA	-0.042	-0.006	-0.036	-1.126	0.263

Panel E: Difference-in-Differences Estimator of Q						
Treatment		Control		Difference-in-differences	t-statistic	p-value
Before	After	Before	After			
2.075	1.464	1.698	2.235	-1.155	-4.259	0.000

Table IX - *Continued*

Panel F: Difference-in-Differences Regressions		
	Q	
	(1)	(2)
TREAT×AFTER	-0.924***	-0.945***
	(-3.130)	(-3.236)
TREAT	0.262	0.199
	(1.244)	(0.996)
AFTER	0.413**	0.399**
	(2.266)	(2.170)
BLOCK	-0.066	-0.176**
	(-0.776)	(-2.133)
SIZE	0.774***	0.721***
	(8.467)	(7.384)
TURNOVER	1.924*	1.091
	(1.908)	(1.094)
IO	-1.361	-1.910**
	(-1.431)	(-2.114)
ANALYST	-0.297**	-0.074
	(-2.249)	(-0.620)
LTD	-0.661	-0.790
	(-1.083)	(-1.438)
CAPX	-0.763	-1.158**
	(-1.021)	(-1.980)
IDIO	28.106***	22.348***
	(3.897)	(3.031)
DIVD	-0.659***	-0.410**
	(-2.680)	(-2.116)
ROA	-0.391*	-0.435*
	(-1.912)	(-1.950)
Fixed effects	Industry1	Industry2
No. of obs.	368	368
R^2	40.54%	33.82%
Adjusted R^2	36.54%	30.39%

Table X
Underlying Mechanism Test in the Study of Firm Valuation: Stock Liquidity Mechanism

This table tests the underlying mechanism of stock liquidity for dark trading activities and block trading activities to affect firm valuation. It adopts interaction terms of *DARK* and *BLOCK* with variables related to stock liquidity and allows for the effects of *DARK* and *BLOCK* to vary with stock liquidity. *SPREAD* denotes average quoted bid-ask spread, defined as the absolute difference between best bid and ask price divided by the mid-point of the best bid and ask price. *SPREAD* decreases with stock liquidity and is an illiquidity measure. *ZERORET* is defined as the number of the days with zero returns divided by the total number of trading days over the fiscal year. A higher *ZERORET* indicates lower stock liquidity. Dependent variable is Tobin's Q (*Q*), calculated by using market value of assets divided by book value of total assets. Definitions of the other variables are provided in Table I. Panel A reports the regression results for examining stock liquidity as the underlying mechanism for dark trading activities to affect firm valuation. *DARK×SPREAD* (*DARK×ZERORET*) is the interaction term of *DARK* and *SPREAD* (*ZERORET*). Panel B reports the regression results for examining stock liquidity as the underlying mechanism for block trading activities to affect firm valuation. *BLOCK×SPREAD* (*BLOCK×ZERORET*) is the interaction term of *BLOCK* and *SPREAD* (*ZERORET*). Industry fixed effects are constructed based on either 2-digit GICS code (Industry1) or General Industry Classification (Industry2). t-statistics calculated based on heteroskedasticity-consistent standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Testing Stock Liquidity Mechanism of Dark Trading

	Q			
	(1)	(2)	(3)	(4)
DARK	-0.128*	-0.040	-0.095	-0.019
	(-1.648)	(-0.512)	(-1.145)	(-0.226)
BLOCK	-0.048	-0.097**	-0.046	-0.089*
	(-0.991)	(-1.977)	(-0.925)	(-1.786)
DARK×SPREAD	-2.751*	-3.724**		
	(-1.731)	(-2.274)		
SPREAD	-12.305*	-12.246*		
	(-1.855)	(-1.784)		
DARK×ZERORET			-0.423***	-0.432***
			(-2.907)	(-2.934)
ZERORET			-2.095***	-2.530***
			(-3.426)	(-4.138)
SIZE	0.370***	0.318***	0.357***	0.278***
	(9.774)	(8.871)	(9.427)	(7.912)
TURNOVER	0.290	-0.232	0.277	-0.187
	(0.219)	(-0.168)	(0.211)	(-0.137)
IO	-1.733***	-2.000***	-1.767***	-2.059***
	(-4.266)	(-4.964)	(-4.332)	(-5.082)
ANALYST	-0.118**	0.041	-0.125**	0.010
	(-2.194)	(0.765)	(-2.344)	0.197
LTD	-1.201***	-1.534***	-1.213***	-1.531***
	(-5.628)	(-6.746)	(-5.675)	(-6.694)
CAPX	0.868*	-0.302	0.866*	-0.336
	(1.787)	(-0.661)	(1.759)	(-0.722)
IDIO	27.807***	20.912***	24.894***	19.281***
	(5.194)	(4.004)	(4.900)	(3.789)
DIVD	-0.135	-0.095	-0.160	-0.128
	(-1.119)	(-0.771)	(-1.342)	(-1.051)
ROA	-1.113***	-1.154***	-1.103***	-1.144***
	(-4.830)	(-4.771)	(-4.829)	(-4.779)
Fixed effects	Industry1, Year	Industry2, Year	Industry1, Year	Industry2, Year
No. of obs.	3,687	3,687	3,687	3,687
R^2	19.79%	15.28%	19.90%	15.50%
Adjusted R^2	19.07%	14.63%	19.18%	14.85%

Table X - *Continued*

Panel B: Testing Stock Liquidity Mechanism of Block Trading				
	Q			
	(1)	(2)	(3)	(4)
DARK	-0.190**	-0.124	-0.197***	-0.122*
	(-2.507)	(-1.641)	(-2.648)	(-1.657)
BLOCK	0.002	-0.036	-0.009	-0.055
	(0.033)	(-0.727)	(-0.178)	(-1.081)
BLOCK×SPREAD	-1.717	-1.982		
	(-1.148)	(-1.248)		
SPREAD	-12.248	-10.808		
	(-1.288)	(-1.081)		
BLOCK×ZERORET			-0.109	-0.091
			(-0.860)	(-0.703)
ZERORET			-1.177*	-1.506**
			(-1.645)	(-2.078)
SIZE	0.362***	0.305***	0.346***	0.268***
	(9.560)	(8.596)	(9.180)	(7.631)
TURNOVER	0.281	-0.256	0.292	-0.169
	(0.212)	(-0.184)	(0.221)	(-0.123)
IO	-1.716***	-1.963***	-1.744***	-2.034***
	(-4.229)	(-4.878)	(-4.271)	(-5.022)
ANALYST	-0.133**	0.021	-0.137***	-0.002
	(-2.480)	(0.397)	(-2.589)	(-0.037)
LTD	-1.221***	-1.565***	-1.199***	-1.521***
	(-5.701)	(-6.851)	(-5.599)	(-6.626)
CAPX	0.880*	-0.296	0.873*	-0.329
	(1.811)	(-0.648)	(1.768)	(-0.707)
IDIO	28.107***	21.359***	24.398***	18.753***
	(5.288)	(4.123)	(4.809)	(3.692)
DIVD	-0.142	-0.106	-0.169	-0.137
	(-1.176)	(-0.857)	(-1.410)	(-1.126)
ROA	-1.110***	-1.148***	-1.099***	-1.139***
	(-4.806)	(-4.744)	(-4.813)	(-4.758)
Fixed effects	Industry1, Year	Industry2, Year	Industry1, Year	Industry2, Year
No. of obs.	3,687	3,687	3,687	3,687
R^2	19.74%	15.16%	19.73%	15.31%
Adjusted R^2	19.02%	14.52%	19.00%	14.66%

Table XI

Underlying Mechanism Test in the Study of Firm Valuation: Information Efficiency Mechanism

This table tests the underlying mechanism of information efficiency for dark trading activities and block trading activities to affect firm valuation. It adopts interaction terms of *DARK* and *BLOCK* with variables related to information efficiency and allows for the effects of *DARK* and *BLOCK* to vary with a stock's information efficiency. Price delay (*DELAY*) is measured by using 1 minus the ratio of R^2 with restrictions over R^2 without restrictions. The unrestricted R^2 is the R-squared obtained from regressing daily stock return on the concurrent market index return and lagged market returns up to 4 days. The restricted R^2 is the R-squared obtained from regressing daily stock return on the concurrent market index return only. Price delay measure reflects the level of information inefficiency of the stock with larger *DELAY* presenting lower information efficiency. *AUTOCOR* is the absolute value of autocorrelation in stock daily returns, and a larger *AUTOCOR* indicates lower information efficiency. Dependent variable is Tobin's Q (*Q*), calculated by using market value of assets divided by book value of total assets. Definitions of the other variables are provided in Table I. Panel A reports the regression results for examining information efficiency as the underlying mechanism for dark trading activities to affect firm valuation. *DARK×DELAY* (*DARK×AUTOCOR*) is the interaction term of *DARK* and *DELAY* (*AUTOCOR*). Panel B reports the regression results for examining information efficiency as the underlying mechanism for block trading activities to affect firm valuation. *BLOCK×DELAY* (*BLOCK×AUTOCOR*) is the interaction term of *BLOCK* and *DELAY* (*AUTOCOR*). Industry fixed effects are constructed based on either 2-digit GICS code (Industry1) or General Industry Classification (Industry2). t-statistics calculated based on heteroskedasticity-consistent standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Testing Information Efficiency Mechanism of Dark Trading

	Q			
	(1)	(2)	(3)	(4)
DARK	-0.168**	-0.091	-0.199***	-0.146**
	(-2.141)	(-1.151)	(-2.738)	(-1.987)
BLOCK	-0.035	-0.080	-0.027	-0.068
	(-0.718)	(-1.602)	(-0.577)	(-1.451)
DARK×DELAY	-0.078	-0.090		
	(-1.290)	(-1.483)		
DELAY	-0.382*	-0.200		
	(-1.714)	(-0.894)		
DARK×AUTOCOR			-0.101	0.044
			(-0.310)	(0.129)
AUTOCOR			-0.222	0.417
			(-0.166)	(0.307)
SIZE	0.368***	0.325***	0.374***	0.312***
	(10.089)	(9.340)	(9.904)	(9.042)
TURNOVER	0.192	-0.304	0.217	-0.309
	(0.146)	(-0.221)	(0.165)	(-0.225)
IO	-1.711***	-1.935***	-1.666***	-1.908***
	(-4.201)	(-4.800)	(-4.080)	(-4.736)
ANALYST	-0.118**	0.043	-0.116**	0.032
	(-2.239)	(0.805)	(-2.202)	(0.602)
LTD	-1.219***	-1.563***	-1.226***	-1.571***
	(-5.687)	(-6.844)	(-5.653)	(-6.764)
CAPX	0.903*	-0.256	0.921*	-0.266
	(1.832)	(-0.548)	(1.872)	(-0.576)
IDIO	25.423***	20.246***	25.274***	20.002***
	(5.046)	(4.039)	(5.035)	(3.985)
DIVD	-0.149	-0.126	-0.159	-0.126
	(-1.234)	(-1.014)	(-1.326)	(-1.038)
ROA	-1.094***	-1.140***	-1.097***	-1.135***
	(-4.805)	(-4.745)	(-4.795)	(-4.713)
Fixed effects	Industry1, Year	Industry2, Year	Industry1, Year	Industry2, Year
No. of obs.	3,687	3,687	3,687	3,687
R^2	19.68%	15.16%	19.63%	15.08%
Adjusted R^2	18.96%	14.15%	18.19%	14.43%

Table XI - *Continued*

Panel B: Testing Information Efficiency Mechanism of Block Trading				
	Q			
	(1)	(2)	(3)	(4)
DARK	-0.211***	-0.140*	-0.211***	-0.141**
	(-2.870)	(-1.912)	(-2.921)	(-1.962)
BLOCK	-0.030	-0.074	-0.003	-0.060
	(-0.605)	(-1.454)	(-0.058)	(-1.221)
BLOCK×DELAY	0.015	0.019		
	(0.309)	(0.376)		
DELAY	-0.026	0.218		
	(-0.108)	(0.884)		
BLOCK×AUTOCOR			-0.224	-0.091
			(-0.897)	(-0.347)
AUTOCOR			-0.879	-0.142
			(-0.887)	(-0.134)
SIZE	0.365***	0.321***	0.375***	0.312***
	(10.053)	(9.306)	(9.841)	(9.038)
TURNOVER	0.213	-0.280	0.219	-0.314
	(0.161)	(-0.203)	(0.167)	(-0.228)
IO	-1.678***	-1.899***	-1.670***	-1.909***
	(-4.118)	(-4.718)	(-4.080)	(-4.731)
ANALYST	-0.123**	0.037	-0.118**	0.032
	(-2.344)	(0.695)	(-2.233)	(0.599)
LTD	-1.221***	-1.570***	-1.225***	-1.574***
	(-5.683)	(-6.848)	(-5.649)	(-6.805)
CAPX	0.904*	-0.251	0.924*	-0.268
	(1.835)	(-0.537)	(1.879)	(-0.580)
IDIO	25.229***	20.039***	25.471***	20.109***
	(4.999)	(3.990)	(5.032)	(3.990)
DIVD	-0.156	-0.135	-0.155	-0.122
	(-1.296)	(-1.090)	(-1.299)	(-1.010)
ROA	-1.094***	-1.140***	-1.097***	-1.136***
	(-4.804)	(-4.743)	(-4.802)	(-4.720)
Fixed effects	Industry1, Year	Industry2, Year	Industry1, Year	Industry2, Year
No. of obs.	3,687	3,687	3,687	3,687
R^2	19.64%	15.10%	19.65%	15.08%
Adjusted R^2	18.91%	14.45%	18.92%	14.43%

Table XII

Underlying Mechanism Test in the Study of Firm Valuation: Corporate Governance Mechanism

This table tests the underlying mechanism of corporate governance for dark trading activities and block trading activities to affect firm valuation. It adopts interaction terms of *DARK* and *BLOCK* with variables related to block ownership and allows for the effects of *DARK* and *BLOCK* to vary with a stock's block ownership. *BLOCKO* measures aggregate percentage ownership of blockholders who hold at least 5% of total common shares outstanding. *NBLOCK* represents number of blockholders who hold at least 5% of total common shares outstanding. Dependent variable is Tobin's Q (*Q*), calculated by using market value of assets divided by book value of total assets. Definitions of the other variables are provided in Table I. Panel A reports the regression results for examining corporate governance as the underlying mechanism for dark trading activities to affect firm valuation. *DARK×BLOCKO* (*DARK×NBLOCK*) is the interaction term of *DARK* and *BLOCKO* (*NBLOCK*). Panel B reports the regression results for examining corporate governance as the underlying mechanism for block trading activities to affect firm valuation. *BLOCK×BLOCKO* (*BLOCK×NBLOCK*) is the interaction term of *BLOCK* and *BLOCKO* (*NBLOCK*). Industry fixed effects are constructed based on either 2-digit GICS code (Industry1) or General Industry Classification (Industry2). t-statistics calculated based on heteroskedasticity-consistent standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Testing Corporate Governance Mechanism of Dark Trading				
	Q			
	(1)	(2)	(3)	(4)
DARK	-0.217***	-0.133*	-0.217***	-0.140*
	(-2.989)	(-1.855)	(-2.881)	(-1.870)
BLOCK	-0.008	-0.036	-0.011	-0.038
	(-0.199)	(-0.850)	(-0.253)	(-0.886)
DARK×BLOCKO	0.005	0.003		
	(1.049)	(0.743)		
BLOCKO	0.016	0.013		
	(1.311)	(1.078)		
DARK×NBLOCK			0.051	0.049
			(1.152)	(1.095)
NBLOCK			0.172	0.187
			(1.399)	(1.517)
SIZE	0.369***	0.307***	0.372***	0.312***
	(10.730)	(9.780)	(10.887)	(9.944)
TURNOVER	0.275	-0.280	0.251	-0.301
	(0.208)	(-0.203)	(0.190)	(-0.218)
IO	-1.542***	-1.822***	-1.578***	-1.873***
	(-4.028)	(-4.845)	(-4.127)	(-4.973)
ANALYST	-0.126***	-0.015	-0.128***	-0.017
	(-2.586)	(-0.305)	(-2.616)	(-0.349)
LTD	-1.156***	-1.419***	-1.164***	-1.427***
	(-5.740)	(-6.825)	(-5.740)	(-6.820)
CAPX	1.062**	-0.104	1.056**	-0.106
	(2.343)	(-0.239)	(2.319)	(-0.242)
IDIO	24.556***	24.665***	19.924***	20.097***
	(5.088)	(5.094)	(4.255)	(4.280)
DIVD	-0.184*	-0.121	-0.186*	-0.126
	(-1.657)	(-1.093)	(-1.672)	(-1.122)
ROA	-1.068***	-1.106***	-1.084***	-1.118***
	(-4.853)	(-4.766)	(-4.818)	(-4.732)
Fixed effects	Industry1, Year	Industry2, Year	Industry1, Year	Industry2, Year
No. of obs.	3,687	3,687	3,687	3,687
R^2	20.15%	15.08%	20.08%	15.06%
Adjusted R^2	19.47%	14.47%	19.40%	14.45%

Table XII - *Continued*

Panel B: Testing Corporate Governance Mechanism of Block Trading

	Q			
	(1)	(2)	(3)	(4)
DARK	-0.206***	-0.126*	-0.212***	-0.133*
	(-2.873)	(-1.779)	(-2.915)	(-1.853)
BLOCK	0.010	-0.021	0.015	-0.015
	(0.250)	(-0.504)	(0.343)	(-0.337)
BLOCK×BLOCKO	-0.002	-0.002		
	(-1.168)	(-0.875)		
BLOCKO	-0.004	-0.001		
	(-0.614)	(-0.201)		
BLOCK×NBLOCK			-0.035	-0.031
			(-1.609)	(-1.413)
NBLOCK			-0.069	-0.037
			(-1.121)	(-0.585)
SIZE	0.365***	0.305***	0.369***	0.310***
	(10.614)	(9.604)	(10.759)	(9.795)
TURNOVER	0.290	-0.269	0.274	-0.286
	(0.219)	(-0.195)	(0.207)	(-0.207)
IO	-1.549***	-1.830***	-1.603***	-1.895***
	(-4.042)	(-4.855)	(-4.190)	(-5.028)
ANALYST	-0.127***	-0.015	-0.129***	-0.018
	(-2.607)	(-0.313)	(-2.650)	(-0.371)
LTD	-1.152***	-1.417***	-1.158***	-1.422***
	(-5.731)	(-6.821)	(-5.720)	(-6.809)
CAPX	1.052**	-0.111	1.045**	-0.115
	(2.354)	(-0.258)	(2.315)	(-0.267)
IDIO	24.533***	19.903***	24.737***	20.161***
	(5.079)	(4.247)	(5.103)	(4.291)
DIVD	-0.175	-0.115	-0.178	-0.118
	(-1.555)	(-1.020)	(-1.577)	(-1.037)
ROA	-1.082***	-1.116***	-1.088***	-1.122***
	(-4.859)	(-4.761)	(-4.854)	(-4.770)
Fixed effects	Industry1, Year	Industry2, Year	Industry1, Year	Industry2, Year
No. of obs.	3,687	3,687	3,687	3,687
R^2	20.18%	15.10%	20.14%	15.11%
Adjusted R^2	19.50%	14.49%	19.46%	14.49%

Table XIII

Difference-in-Differences Estimators of Underlying Mechanisms in the Study of Firm Valuation

This table reports the difference-in-differences estimator of variables related to stock liquidity, information efficiency, and corporate governance, respectively, based on the matched sample from the difference-in-differences test in Table IX where the removal of the ten-second rule in 2009 is adopted as an exogenous shock to dark trading activities. Variables related to stock liquidity include quoted bid-ask spread (*SPREAD*) and proportion of days with zero returns (*ZERORET*) and both of them decreases with liquidity. *SPREAD* is calculated as the absolute difference between best bid and ask price divided by the mid-point of the best bid and ask price. *SPREAD* decreases with stock liquidity and is an illiquidity measure. *ZERORET* is calculated as the number of the days with zero returns divided by the total number of trading days over the fiscal year. Variables related to information efficiency include price delay measure (*DELAY*) and absolute stock return autocorrelation (*AUTOCOR*) and both of them proxies for information inefficiency. *DELAY* is measured by using 1 minus the ratio of R^2 with restrictions over R^2 without restrictions. The unrestricted R^2 is the R-squared obtained from regressing daily stock return on the concurrent market index return and lagged market returns up to 4 days. The restricted R^2 is the R-squared obtained from regressing daily stock return on the concurrent market index return only. *AUTOCOR* is the absolute value of autocorrelation in stock daily returns. Variables of corporate governance include blockholder ownership (*BLOCKO*) and number of blockholders (*NBLOCK*). *BLOCKO* measures aggregate percentage ownership of blockholders who hold at least 5% of total common shares outstanding. *NBLOCK* is number of blockholders who hold at least 5% of total common shares outstanding. Following Table IX, we rank all sample firms based on their changes in dark trades surrounding the rule removal, and select the top 30% of the firms as treatment group and the bottom 30% of the firms as control group. We then run a probit model with the dependent variable being a dummy variable that is set to one for the firm in the treatment group and 0 in the control group. Propensity scores are used as predicted probabilities to match firms in two groups by closest propensity score match. This table reports the average variables in treatment group and control group in the year before event year (i.e., in year 2008) and the year after event year (i.e., in year 2010), respectively. It also reports difference-in-differences estimator of the variables based on the matched sample, as well as the corresponding t-statistics and p-values of the differences.

	Treatment		Control		Difference-in-differences	t-statistic	p-value
Variable	Before	After	Before	After			
SPREAD	0.018	0.023	0.026	0.016	0.014	7.148	0.000
ZERORET	0.163	0.213	0.161	0.150	0.060	5.168	0.000
DELAY	0.291	0.340	0.270	0.256	0.064	1.647	0.103
AUTOCOR	0.088	0.098	0.083	0.075	0.019	1.373	0.173
BLOCKO	25.882	19.296	34.775	12.191	15.997	3.922	0.000
NBLOCK	2.253	1.571	2.912	0.758	1.473	4.465	0.000

Table XIV
Residual Effect of Dark Trading on Firm Valuation after Controlling for Possible Mechanisms

This table reports the regression results of difference-in-differences of firm valuation (*Q*) after controlling for possible mechanisms of stock liquidity and blockholder ownership based on the matched sample from the difference-in-differences test in Table IX where the removal of the ten-second rule in 2009 is adopted as an exogenous shock to dark trading activities. Variables related to stock liquidity include quoted bid-ask spread (*SPREAD*) and proportion of days with zero returns (*ZERORET*) and both of them decreases with liquidity. *SPREAD* is calculated as the absolute difference between best bid and ask price divided by the mid-point of the best bid and ask price. *SPREAD* decreases with stock liquidity and is an illiquidity measure. *ZERORET* is calculated as the number of the days with zero returns divided by the total number of trading days over the fiscal year. Variables of corporate governance include blockholder ownership (*BLOCKO*) and number of blockholders (*NBLOCK*). *BLOCKO* measures aggregate percentage ownership of blockholders who hold at least 5% of total common shares outstanding. *NBLOCK* is number of blockholders who hold at least 5% of total common shares outstanding. Following Table IX, we rank all sample firms based on their changes in dark trades surrounding the rule removal, and select the top 30% of the firms as treatment group and the bottom 30% of the firms as control group. We then run a probit model with the dependent variable being a dummy variable that is set to one for the firm in the treatment group and 0 in the control group. Propensity scores are used as predicted probabilities to match firms in two groups by closest propensity score match. This table reports the regression results based on the matched sample of the year before and the year after the exogenous event. *TREAT* is a dummy variable equal to one if a stock is in the treatment group and zero if in the control group. *AFTER* is a dummy variable equal to one for 2010 (post-event year) and zero for 2008 (pre-event year). *TREAT×AFTER* is the interaction between these two variables. In Panels C and D (Panels E and F), the mechanism of default risk is further controlled with firm default risk measured by one-year expected default frequency *EDF_1y* (five-year expected default frequency *EDF_5y*). Industry fixed effects are constructed based on 2-digit GICS code (Industry1) in Panels A, C, and E, and General Industry Classification (Industry2) in Panels B, D, and F. t-statistics calculated based on heteroskedasticity-consistent standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Difference-in-Differences Regressions with Industry1 as Fixed Effects

	Q				
	(1)	(2)	(3)	(4)	(5)
TREAT×AFTER	-1.149***	-0.957***	-0.887***	-1.062***	-0.999***
	(-3.892)	(-3.115)	(-2.959)	(-3.522)	(-3.380)
TREAT	0.414	0.318	0.298	0.406	0.386
	(1.638)	(1.312)	(1.235)	(1.634)	(1.563)
AFTER	0.538***	0.428*	0.323	0.564**	0.462**
	(2.851)	(1.815)	(1.401)	(2.553)	(2.143)
SPREAD		-15.088**	-15.528***		
		(-2.556)	(-2.654)		
ZERORET				-1.892*	-1.867*
				(-1.928)	(-1.907)
BLOCKO		0.002		0.003	
		(0.506)		(0.766)	
NBLOCK			-0.033		-0.024
			(-0.824)		(-0.591)
Fixed effects	Industry1	Industry1	Industry1	Industry1	Industry1
No. of obs.	366	366	366	366	366
R^2	15.17%	17.80%	17.87%	16.97%	16.86%
Adjusted R^2	12.04%	14.27%	14.34%	13.41%	13.28%

Table XIV - *Continued*

Panel B: Difference-in-Differences Regressions with Industry2 as Fixed Effects

	Q				
	(1)	(2)	(3)	(4)	(5)
TREAT×AFTER	-1.149***	-0.989***	-0.903***	-1.063***	-0.987***
	(-3.749)	(-3.075)	(-2.882)	(-3.376)	(-3.207)
TREAT	0.325	0.218	0.198	0.319	0.301
	(1.370)	(0.941)	(0.861)	(1.354)	(1.290)
AFTER	0.538***	0.446*	0.315	0.553**	0.430*
	(2.703)	(1.841)	(1.311)	(2.399)	(1.892)
SPREAD		-12.385**	-12.931**		
		(-2.172)	(-2.292)		
ZERORET				-1.752*	-1.730*
				(-1.734)	(-1.725)
BLOCKO		0.001		0.002	
		(0.412)		(0.594)	
NBLOCK			-0.049		-0.041
			(-1.150)		(-0.948)
Fixed effects	Industry2	Industry2	Industry2	Industry2	Industry2
No. of obs.	366	366	366	366	366
R^2	7.22%	9.04%	9.34%	8.71%	8.83%
Adjusted R^2	5.15%	6.47%	6.77%	6.13%	6.25%

Panel C: Difference-in-Differences Regressions with EDF_1y controlled and Industry1 as Fixed Effects

	Q				
	(1)	(2)	(3)	(4)	(5)
TREAT×AFTER	-1.190***	-1.027***	-0.963***	-1.112***	-1.055***
	(-4.084)	(-3.367)	(-3.224)	(-3.737)	(-3.610)
TREAT	0.482*	0.399	0.378	0.486**	0.467*
	(1.932)	(1.648)	(1.572)	(1.979)	(1.910)
AFTER	0.445**	0.372	0.280	0.481**	0.392*
	(2.365)	(1.605)	(1.236)	(2.200)	(1.841)
EDF_1y	-1.077***	-0.963***	-0.945***	-1.111***	-1.099***
	(-4.171)	(-3.380)	(-3.276)	(-4.131)	(-4.064)
SPREAD		-13.511**	-13.937**		
		(-2.265)	(-2.349)		
ZERORET				-1.995**	-1.967**
				(-2.087)	(-2.064)
BLOCKO		0.002		0.003	
		(0.552)		(0.805)	
NBLOCK			-0.025		-0.016
			(-0.634)		(-0.403)
Fixed effects	Industry1	Industry1	Industry1	Industry1	Industry1
No. of obs.	366	366	366	366	366
R^2	17.82%	19.80%	19.79%	19.66%	19.48%
Adjusted R^2	14.54%	16.11%	16.10%	15.97%	15.78%

Table XIV - *Continued*

Panel D: Difference-in-Differences Regressions with EDF_1y controlled and Industry2 as Fixed Effects

	Q				
	(1)	(2)	(3)	(4)	(5)
TREAT×AFTER	-1.199***	-1.078***	-1.003***	-1.130***	-1.065***
	(-3.988)	(-3.402)	(-3.234)	(-3.659)	(-3.515)
TREAT	0.425*	0.342	0.319	0.435*	0.416*
	(1.821)	(1.481)	(1.394)	(1.868)	(1.796)
AFTER	0.426**	0.375	0.267	0.460**	0.359
	(2.126)	(1.573)	(1.132)	(2.009)	(1.595)
EDF_1y	-1.307***	-1.240***	-1.207***	-1.322***	-1.295***
	(-5.116)	(-4.446)	(-4.172)	(-4.945)	(-4.697)
SPREAD		-10.617*	-11.100**		
		(-1.880)	(-1.971)		
ZERORET				-1.775*	-1.747*
				(-1.800)	(-1.786)
BLOCKO		0.002		0.002	
		(0.521)		(0.702)	
NBLOCK			-0.035		-0.027
			(-0.812)		(-0.625)
Fixed effects	Industry2	Industry2	Industry2	Industry2	Industry2
No. of obs.	366	366	366	366	366
R^2	11.28%	12.52%	12.60%	12.70%	12.63%
Adjusted R^2	9.04%	9.79%	9.88%	9.98%	9.91%

Panel E: Difference-in-Differences Regressions with EDF_5y controlled and Industry1 as Fixed Effects

	Q				
	(1)	(2)	(3)	(4)	(5)
TREAT×AFTER	-1.031***	-0.854***	-0.788***	-0.941***	-0.881***
	(-3.635)	(-2.946)	(-2.797)	(-3.328)	(-3.197)
TREAT	0.430*	0.344	0.323	0.430*	0.409*
	(1.778)	(1.488)	(1.404)	(1.829)	(1.749)
AFTER	0.086	-0.004	-0.101	0.115	0.021
	(0.426)	(-0.018)	(-0.446)	(0.515)	(0.097)
EDF_5y	-1.159***	-1.156***	-1.147***	-1.194***	-1.184***
	(-5.449)	(-5.469)	(-5.474)	(-5.678)	(-5.679)
SPREAD		-14.972***	-15.402***		
		(-2.608)	(-2.698)		
ZERORET				-2.132**	-2.099**
				(-2.321)	(-2.289)
BLOCKO		0.002		0.003	
		(0.655)		(0.934)	
NBLOCK			-0.025		-0.016
			(-0.657)		(-0.411)
Fixed effects	Industry1	Industry1	Industry1	Industry1	Industry1
No. of obs.	366	366	366	366	366
R^2	22.67%	25.22%	25.17%	24.86%	24.61%
Adjusted R^2	19.59%	21.78%	21.73%	21.41%	21.15%

Table XIV - *Continued*

Panel F: Difference-in-Differences Regressions with EDF_5y controlled and Industry1 as Fixed Effects

	Q				
	(1)	(2)	(3)	(4)	(5)
TREAT×AFTER	-1.013***	-0.865***	-0.794***	-0.932***	-0.869***
	(-3.496)	(-2.887)	(-2.736)	(-3.193)	(-3.068)
TREAT	0.384*	0.287	0.266	0.390*	0.372*
	(1.765)	(1.358)	(1.272)	(1.815)	(1.742)
AFTER	0.019	-0.059	-0.162	0.046	-0.051
	(0.089)	(-0.247)	(-0.711)	(0.200)	(-0.233)
EDF_5y	-1.332***	-1.338***	-1.324***	-1.351***	-1.338***
	(-6.261)	(-6.304)	(-6.179)	(-6.374)	(-6.251)
SPREAD		-12.693**	-13.112**		
		(-2.349)	(-2.436)		
ZERORET				-1.917**	-1.885**
				(-2.056)	(-2.036)
BLOCKO		0.002		0.003	
		(0.583)		(0.781)	
NBLOCK			-0.032		-0.023
			(-0.796)		(-0.575)
Fixed effects	Industry2	Industry2	Industry2	Industry2	Industry2
No. of obs.	366	366	366	366	366
R^2	17.53%	19.38%	19.42%	19.24%	19.11%
Adjusted R^2	15.44%	16.87%	16.91%	16.72%	16.59%

Table XV
Effects of Dark and Block Trading Activities on Firm Default Risk

This table reports the regression results for examining the effects of dark trading and block trading on firm default risk. The dependent variable is one-year expected default frequency (*EDF_1y*) or five-year expected default frequency (*EDF_5y*). *DARK* (*BLOCK*) denotes the natural logarithm of dark (block) trading ratio that is the dollar volume of dark (block) trades as a percentage of the total dollar volume. All independent variables are lagged by 1 year. Control variable *Ln(EQUITY)* is the natural logarithm of market value of equity, *Ln(DEBT)* is the natural logarithm of face value of debt, $1/\sigma_E$ is the inverse of annualized stock return volatility, *EX_RET* is annual excess return, and *ROA* is the return of asset. Definitions of the variables are also provided in Table III. Industry fixed effects are constructed based on 2-digit GICS code (GICS). Panels A and B examine the effects of *DARK* and *BLOCK* on firm default risk, respectively, while Panel C includes both *DARK* and *BLOCK* as independent variables. t-statistics calculated based on heteroskedasticity-consistent standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Effect of Dark Trading on Firm Default Risk

	EDF_1y			*EDF_5y*		
	(1)	(2)	(3)	(4)	(5)	(6)
DARK	0.003***	0.003***	0.003**	0.005***	0.006***	0.004*
	(8.746)	(9.952)	(2.465)	(9.777)	(10.987)	(1.775)
Ln(EQUITY)	-0.018***	-0.017***	-0.017***	-0.021***	-0.022***	-0.023***
	(-9.283)	(-8.355)	(-8.575)	(-6.609)	(-6.615)	(-6.965)
Ln(DEBT)	0.008***	0.007***	0.007***	0.016***	0.016***	0.016***
	(20.206)	(18.619)	(18.891)	(25.813)	(25.484)	(24.417)
$1/\sigma_E$	-0.014***	-0.016***	-0.019***	-0.036***	-0.027***	-0.036***
	(-5.700)	(-5.833)	(-6.385)	(-8.471)	(-5.890)	(-7.360)
EX_RET	-0.000	-0.000***	-0.000**	-0.000	-0.000***	-0.000
	(-0.209)	(-6.003)	(-5.625)	(-0.326)	(-7.606)	(-0.426)
ROA	-0.001	-0.001	-0.001	-0.002*	-0.002	-0.002*
	(-0.955)	(-0.594)	(-0.506)	(-1.841)	(-1.134)	(-1.732)
Fixed effects	None	GICS	GICS, Year	None	GICS	GICS, Year
No. of obs.	6,049	6,049	6,049	6,049	6,049	6,049
R^2	8.54%	10.08%	12.95%	12.40%	13.21%	18.04%
Adjusted R^2	8.45%	9.84%	12.58%	12.32%	12.98%	17.68%

Panel B: Effect of Block Trading on Firm Default Risk

	EDF_1y			*EDF_5y*		
	(1)	(2)	(3)	(4)	(5)	(6)
BLOCK	0.002***	0.002***	0.001**	0.004***	0.004***	0.001
	(6.963)	(6.660)	(2.057)	(7.775)	(8.021)	(0.547)
Ln(EQUITY)	-0.017***	-0.016***	-0.018***	-0.021***	-0.021***	-0.023***
	(-9.024)	(-7.986)	(-8.618)	(-6.357)	(-6.219)	(-6.760)
Ln(DEBT)	0.008***	0.007***	0.007***	0.016***	0.016***	0.016***
	(20.291)	(18.578)	(18.894)	(25.885)	(25.395)	(26.028)
$1/\sigma_E$	-0.015***	-0.018***	-0.019***	-0.038***	-0.031***	-0.036***
	(-6.123)	(-6.362)	(-6.365)	(-8.931)	(-6.616)	(-7.300)
EX_RET	-0.000	-0.000***	-0.000***	-0.000	-0.000***	-0.000***
	(-0.290)	(-7.282)	(-5.818)	(-0.416)	(-9.340)	(-7.151)
ROA	-0.001	-0.001	-0.001	-0.002*	-0.002	-0.002
	(-0.966)	(-0.603)	(-0.509)	(-1.850)	(-1.102)	(-1.109)
Fixed effects	None	GICS	GICS, Year	None	GICS	GICS, Year
No. of obs.	6,049	6,049	6,049	6,049	6,049	6,049
R^2	8.12%	9.67%	12.95%	11.90%	12.64%	18.00%
Adjusted R^2	8.03%	9.43%	12.58%	11.81%	12.40%	17.65%

Table XV - *Continued*

Panel C: Effects of Dark Trading and Block Trading on Firm Default Risk						
	EDF_1y			*EDF_5y*		
	(1)	(2)	(3)	(4)	(5)	(6)
DARK	0.003***	0.003***	0.002*	0.005***	0.005***	0.004*
	(5.353)	(5.338)	(1.668)	(5.988)	(6.304)	(1.673)
BLOCK	0.000	0.000	0.001	0.001	0.001	-0.000
	(0.932)	(0.681)	(1.385)	(1.036)	(0.921)	(-0.040)
Ln(EQUITY)	-0.018***	-0.017***	-0.018***	-0.022***	-0.023***	-0.023***
	(-9.320)	(-8.343)	(-8.589)	(-6.690)	(-6.694)	(-6.850)
Ln(DEBT)	0.008***	0.007***	0.007***	0.016***	0.016***	0.016***
	(20.222)	(18.644)	(18.894)	(25.831)	(25.490)	(24.415)
$1/\sigma_E$	-0.014***	-0.016***	-0.019***	-0.035***	-0.027***	-0.036***
	(-5.543)	(-5.663)	(-6.394)	(-8.280)	(-5.722)	(-7.360)
EX_RET	-0.000	-0.000***	-0.000***	-0.000	-0.000***	-0.000
	(-0.209)	(-5.971)	(-5.739)	(-0.327)	(-7.575)	(-0.425)
ROA	-0.001	-0.001	-0.001	-0.002*	-0.002	-0.002*
	(-0.952)	(-0.593)	(-0.505)	(-1.838)	(-1.133)	(-1.732)
Fixed effects	None	GICS	GICS, Year	None	GICS	GICS, Year
No. of obs.	6,049	6,049	6,049	6,049	6,049	6,049
R^2	8.55%	10.09%	12.98%	12.42%	13.22%	18.04%
Adjusted R^2	8.44%	9.83%	12.59%	12.32%	12.98%	17.67%

Table XVI

Endogeneity Test in the Study of Firm Default Risk: Two-Stage Least Squares (2SLS)

This table reports the 2SLS regression results for the effects of dark trading and block trading on firm default risk. In the first-stage regression, *DARK* is regressed on two instrumental variables, variable of block trading (*BLOCK*), and control variables. Following Comerton-Forde and Putninš (2015), we construct instrumental variables based on market structure changes that are exogenous with respect to firm valuation but influence the amount of dark trading. The market structure changes include: (i) the removal of the ten-second rule on November 30, 2009 which makes it easier to execute dark trades; and (ii) the change in ASX trading fees on July 1, 2010 which changes the relative explicit costs of trading in the dark compared to trading in the CLOB. We construct a dummy variable $D^{rule\ remove}$ ($D^{fee\ reduce}$) that equals to 1 if the end of the fiscal year is after November 30, 2009 (July 1, 2010) and zero before. Definitions of the other variables are provided in Table III. All the variables are one year lagged and Column 1 reports the results of the first-stage regressions. In the second-stage regression, firm default risk (one-year or five-year expected default frequency, *EDF_1y* or *EDF_5y*) is regressed on the fitted value of dark trading (*PRE_DARK*) as well as variable of block trading (*BLOCK*) and all the lagged control variables, and the results are reported in Columns 2 and 3. Industry fixed effects are constructed based on 2-digit GICS code (GICS). t-statistics calculated based on heteroskedasticity-consistent standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	First-Stage Regression	Second-Stage Regression	
	DARK	*EDF_1y*	*EDF_5y*
	(1)	(2)	(3)
$D^{rule\ remove}$	9.608***		
	(51.303)		
$D^{fee\ reduce}$	1.332***		
	(14.586)		
PRE_DARK		0.022***	0.015*
		(4.787)	(1.889)
BLOCK	0.374***	-0.007***	-0.005
	(26.354)	(-3.592)	(-1.295)
Ln(EQUITY)	0.061*	-0.021***	-0.025***
	(1.749)	(-6.160)	(-7.851)
Ln(DEBT)	-0.013	0.008***	0.017***
	(-1.192)	(6.042)	(7.481)
$1/\sigma_E$	-0.119	-0.015***	-0.032***
	(-1.040)	(-3.269)	(-2.916)
EX_RET	-0.000***	-0.000	-0.000**
	(-7.537)	(-0.190)	(-2.007)
ROA	-0.004	-0.001	-0.002
	(-0.386)	(-1.212)	(-1.100)
Fixed effects	GICS	GICS	GICS
No. of obs.	6,049	6,049	6,049
R^2	75.65%	13.80%	17.91%
Adjusted R^2	75.59%	13.43%	17.56%
F-statistic	1,100		
F-test (p-value)	0.000		

Table XVII
Endogeneity Test in the Study of Firm Default Risk: Difference-in-Differences Test

This table shows the difference-in-differences test of the effects of dark trading on firm default risk surrounding the year of 2009 when the removal of the ten-second rule occurs. The rule removal makes it easier to execute dark trades and is adopted as an exogenous shock to dark trading activities. We rank all sample firms based on their changes in dark trades surrounding the rule removal, and select the top 45% of the firms as treatment group and the bottom 45% of the firms as control group. We then run a probit model with the dependent variable being a dummy variable that is set to one for the firm in the treatment group and 0 in the control group. The independent variables include dark trading (*DARK*), block trading (*BLOCK*), and all the control variables used in baseline specification, and they are measured prior to the rule removal in year 2008. Definitions of the variables are also provided in Table III. Propensity scores are used as predicted probabilities to match firms in two groups by closest propensity score match. Column 1 in Panel A reports regressions of estimating the probit model before match, while Column 2 reports the probit regression results after matching treatment group with control group. z-statistics are reported in parentheses. Panel B reports the statistical distributions of the propensity scores in treatment group, control group, and the differences between two groups in the matched sample. Panel C reports the average variables in treatment group, control group, and the differences in the averages of every variables in the year before event year (i.e., in year 2008). Panel D reports the average variables in treatment group, control group, and the differences in the averages of every variables in the year after event year (i.e., in year 2010). The corresponding t-statistics and p-values of the differences are also reported in Panels C and D. Panel E reports the difference-in-differences estimator of firm default risk (one-year or five-year expected default frequency, *EDF_1y* or *EDF_5y*) based on the matched sample. Panel F reports the regression of difference-in-differences of firm default risk based on the matched sample. *TREAT* is a dummy variable equal to one if a stock is in the treatment group and zero if in the control group. *AFTER* is a dummy variable equal to one for 2010 (post-event year) and zero for 2008 (pre-event year). *TREAT*AFTER* is the interaction between these two variables. Industry fixed effects are constructed based on 2-digit GICS code (GICS). t-statistics calculated based on heteroskedasticity-consistent standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Probit Regressions with Pre- and Post-Matched Samples

	Before match	After match
	(1)	(2)
DARK	-0.897***	-0.015
	(-3.923)	(-0.142)
BLOCK	0.005	-0.037
	(0.166)	(-1.078)
Ln(EQUITY)	-0.353***	0.082
	(-4.615)	(1.002)
Ln(DEBT)	0.027**	-0.032**
	(2.032)	(-2.446)
$1/\sigma_E$	-0.036	0.185
	(-0.245)	(1.153)
EX_RET	-0.039	-0.017
	(-1.327)	(-0.623)
ROA	0.051	0.000
	(0.757)	(0.004)
Fixed effects	None	None
No. of obs.	442	442
P-value of X^2	0.0000	0.1410
Pseudo R^2	7.15%	1.95%
Log likelihood	-284.452	-300.382

Table XVII - *Continued*

Panel B: Propensity Scores Distribution						
Group	N	Mean	Minimum	Median	Maximum	SD
Treatment	221	0.564	0.069	0.566	0.872	0.127
Control	221	0.561	0.065	0.568	1.000	0.124
Difference	221	0.003	0.004	-0.002	-0.128	0.003

Panel C: Differences in Variables in Pre-Event Year					
	Treatment	Control	Difference	t-statistic	p-value
DARK	-2.655	-2.589	-0.066	-0.690	0.491
BLOCK	-3.953	-3.610	-0.343	-1.161	0.247
Ln(EQUITY)	18.618	18.403	0.215	1.719	0.087
Ln(DEBT)	12.715	14.290	-1.576	-2.362	0.019
$1/\sigma_E$	1.720	1.588	0.132	1.962	0.051
EX_RET	0.179	0.398	-0.219	-0.610	0.542
ROA	0.012	-0.030	0.042	0.228	0.820

Panel D: Differences in Variables in Post-Event Year					
	Treatment	Control	Difference	t-statistic	p-value
DARK	-2.231	-2.765	0.534	4.973	0.000
BLOCK	-4.854	-3.524	-1.330	-3.560	0.000
Ln(EQUITY)	18.447	19.333	-0.886	-5.926	0.000
Ln(DEBT)	12.588	14.189	-1.602	-2.305	0.022
$1/\sigma_E$	1.904	2.088	-0.184	-2.161	0.032
EX_RET	0.651	0.924	-0.272	-1.069	0.286
ROA	-0.046	0.023	-0.070	-2.484	0.014

Panel E: Difference-in-Differences Estimator of Firm Default Risk							
	Treatment		Control		Difference-in-differences	t-statistic	p-value
Variable	Before	After	Before	After			
EDF_1y	0.186	0.076	0.322	0.044	0.169	5.140	0.000
EDF_5y	0.512	0.233	0.594	0.116	0.199	4.485	0.000

Table XVII - *Continued*

Panel F: Difference-in-Differences Regressions		
	EDF_1y	*EDF_5y*
TREAT×AFTER	0.099***	0.118***
	(3.183)	(2.891)
TREAT	-0.084***	-0.027
	(-3.316)	(-0.934)
AFTER	-0.179 ***	-0.367***
	(-7.702)	(-12.743)
BLOCK	0.005***	0.005*
	(2.855)	(1.772)
Ln(EQUITY)	-0.029***	-0.042***
	(-3.476)	(-4.222)
Ln(DEBT)	0.016***	0.029***
	(13.980)	(20.705)
$1/\sigma_E$	-0.137***	-0.118 ***
	(-8.172)	(-5.886)
EX_RET	-0.006*	-0.017***
	(-1.816)	(-2.843)
ROA	0.003	-0.014***
	(0.884)	(-2.707)
Fixed effects	GICS	GICS
No. of obs.	884	884
R^2	45.14%	54.52%
Adjusted R^2	43.94%	53.52%

Table XVIII

Effects of Dark and Block Trading Activities on Firm Default Risk with Control of Firm Valuation

This table reports the regression results for examining the effects of dark trading and block trading on firm default risk after controlling for the effect of firm valuation (*Q*). Tobin's Q (*Q*) is calculated by using market value of assets divided by book value of total assets. The dependent variable is one-year expected default frequency (*EDF_1y*) or five-year expected default frequency (*EDF_5y*). *DARK* (*BLOCK*) denotes the natural logarithm of dark (block) trading ratio that is the dollar volume of dark (block) trades as a percentage of the total dollar volume. All independent variables are lagged by 1 year. Control variable *Ln(EQUITY)* is the natural logarithm of market value of equity, *Ln(DEBT)* is the natural logarithm of face value of debt, $1/\sigma_E$ is the inverse of annualized stock return volatility, *EX_RET* is annual excess return, and *ROA* is the return of asset. Definitions of the variables are also provided in Table III. Industry fixed effects are constructed based on 2-digit GICS code (GICS). Panels A and B examine the effects of *DARK* and *BLOCK* on firm default risk, respectively, while Panel C includes both *DARK* and *BLOCK* as independent variables. t-statistics calculated based on heteroskedasticity-consistent standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Effect of Dark Trading on Firm Default Risk

	EDF_1y			*EDF_5y*		
	(1)	(2)	(3)	(4)	(5)	(6)
DARK	0.003***	0.003***	0.003***	0.005***	0.006***	0.004*
	(8.671)	(3.945)	(6.854)	(9.776)	(5.525)	(1.724)
Q	-0.001	-0.000	-0.002	0.001	0.001	-0.004
	(-1.129)	(-0.175)	(-0.836)	(0.257)	(0.116)	(-0.819)
Ln(EQUITY)	-0.017***	-0.017***	-0.017***	-0.021***	-0.023***	-0.021***
	(-8.824)	(-5.336)	(-4.836)	(-6.509)	(-4.880)	(-4.762)
Ln(DEBT)	0.007***	0.007***	0.007***	0.016***	0.016***	0.016***
	(19.187)	(8.620)	(6.388)	(24.959)	(8.807)	(8.590)
$1/\sigma_E$	-0.015***	-0.016***	-0.020***	-0.035***	-0.027***	-0.037***
	(-5.809)	(-4.473)	(-4.461)	(-8.305)	(-3.237)	(-3.619)
EX_RET	-0.000	-0.000***	-0.000***	-0.000	-0.000***	-0.000***
	(-0.225)	(-4.228)	(-3.163)	(-0.323)	(-5.399)	(-6.909)
ROA	-0.001	-0.001	-0.001*	-0.002*	-0.002	-0.002
	(-1.164)	(-1.016)	(-1.687)	(-1.751)	(-0.892)	(-1.107)
Fixed effects	None	GICS	GICS, Year	None	GICS	GICS, Year
No. of obs.	6,049	6,049	6,049	6,049	6,049	6,049
R^2	8.56%	10.08%	12.99%	12.40%	13.21%	18.08%
Adjusted R^2	8.45%	9.83%	12.60%	12.30%	12.96%	17.71%

Panel B: Effect of Block Trading on Firm Default Risk

	EDF_1y			*EDF_5y*		
	(1)	(2)	(3)	(4)	(5)	(6)
BLOCK	0.002***	0.002**	0.001	0.004***	0.004***	0.001
	(6.914)	(2.371)	(1.058)	(7.770)	(3.618)	(0.308)
Q	-0.002	-0.001	-0.002	-0.000	-0.000	-0.004
	(-1.367)	(-0.347)	(-0.834)	(-0.014)	(-0.022)	(-0.809)
Ln(EQUITY)	-0.017***	-0.016***	-0.017***	-0.021***	-0.021***	-0.022***
	(-8.537)	(-3.975)	(-4.268)	(-6.213)	(-3.529)	(-4.026)
Ln(DEBT)	0.007***	0.007***	0.007***	0.016***	0.016***	0.016***
	(19.205)	(8.809)	(6.422)	(24.955)	(9.023)	(8.575)
$1/\sigma_E$	-0.016***	-0.018***	-0.020***	-0.038***	-0.031***	-0.037***
	(-6.265)	(-3.564)	(-4.495)	(-8.813)	(-2.890)	(-3.604)
EX_RET	-0.000	-0.000***	-0.000***	-0.000	-0.000***	-0.000***
	(-0.308)	(-7.095)	(-2.909)	(-0.417)	(-8.089)	(-6.693)
ROA	-0.001	-0.001	-0.001*	-0.002*	-0.002	-0.002
	(-1.2220	(-1.026)	(-1.838)	(-1.815)	(-0.897)	(-1.105)
Fixed effects	None	GICS	GICS, Year	None	GICS	GICS, Year
No. of obs.	6,049	6,049	6,049	6,049	6,049	6,049
R^2	8.15%	9.67%	12.99%	11.90%	12.64%	18.04%
Adjusted R^2	8.04%	9.42%	12.60%	11.80%	12.39%	17.67%

Table XVIII - *Continued*

Panel C: Effects of Dark Trading and Block Trading on Firm Default Risk						
	EDF_1y			*EDF_5y*		
	(1)	(2)	(3)	(4)	(5)	(6)
DARK	0.003***	0.003**	0.002**	0.005***	0.005***	0.004*
	(5.298)	(2.439)	(2.425)	(5.993)	(3.074)	(1.819)
BLOCK	0.000	0.000	0.001	0.001	0.001	-0.000
	(0.942)	(0.262)	(0.706)	(1.033)	(0.386)	(-0.018)
Q	-0.001	-0.000	-0.002	0.001	0.001	-0.004
	(-1.137)	(-0.185)	(-0.840)	(0.248)	(0.110)	(-0.821)
Ln(EQUITY)	-0.017***	-0.017***	-0.017***	-0.022***	-0.023***	-0.021***
	(-8.869)	(-4.455)	(-4.159)	(-6.590)	(-4.108)	(-3.965)
Ln(DEBT)	0.007***	0.007***	0.007***	0.016***	0.016***	0.016***
	(19.203)	(8.532)	(6.403)	(24.976)	(8.808)	(8.585)
$1/\sigma_E$	-0.014***	-0.016***	-0.020***	-0.035***	-0.027***	-0.037***
	(-5.655)	(-3.900)	(-4.482)	(-8.122)	(-2.868)	(-3.619)
EX_RET	-0.000	-0.000***	-0.000***	-0.000	-0.000***	-0.000***
	(-0.225)	(-4.242)	(-3.376)	(-0.323)	(-5.395)	(-6.725)
ROA	-0.001	-0.001	-0.001*	-0.002*	-0.002	-0.002
	(-1.162)	(-1.018)	(-1.682)	(-1.749)	(-0.894)	(-1.106)
Fixed effects	None	GICS	GICS, Year	None	GICS	GICS, Year
No. of obs.	6,049	6,049	6,049	6,049	6,049	6,049
R^2	8.57%	10.09%	13.02%	12.42%	13.22%	18.08%
Adjusted R^2	8.45%	9.82%	12.61%	12.30%	12.96%	17.70%

Table XIX

Difference-in-Differences Tests in the Study of Firm Default Risk with Control of Firm Valuation

This table reports the difference-in-differences regression of default risk based on the matched sample in Table XVII after controlling for the effect of firm valuation (*Q*). Following Table XVII, the removal of the ten-second rule is adopted as an exogenous shock to dark trading activities. We rank all sample firms based on their changes in dark trades surrounding the rule removal, and select the top 45% of the firms as treatment group and the bottom 45% of the firms as control group. We then run a probit model with the dependent variable being a dummy variable that is set to one for the firm in the treatment group and 0 in the control group. Propensity scores are used as predicted probabilities to match firms in two groups by closest propensity score match. This table reports the regression of difference-in-differences of firm default risk based on the matched sample after controlling for the effect of firm valuation (*Q*). *TREAT* is a dummy variable equal to one if a stock is in the treatment group and zero if in the control group. *AFTER* is a dummy variable equal to one for 2010 (post-event year) and zero for 2008 (pre-event year). *TREAT×AFTER* is the interaction between these two variables. *ΔQ* is the change of Tobin's Q from 2008 to 2010. Definitions of the other variables are provided in Table III. Industry fixed effects are constructed based on 2-digit GICS code (GICS). t-statistics calculated based on heteroskedasticity-consistent standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	EDF_1y		*EDF_5y*	
	(1)	(2)	(3)	(4)
TREAT×AFTER	0.107***	0.107***	0.118***	0.118***
	(3.186)	(3.395)	(2.802)	(2.839)
TREAT	-0.085 ***	-0.084***	-0.010	-0.027
	(-3.675)	(-3.297)	(-0.345)	(-0.933)
AFTER	-0.186***	-0.182***	-0.368***	-0.367***
	(-7.754)	(-7.836)	(-12.278)	(-12.668)
ΔQ×AFTER	0.008	0.011**	0.001	0.000
	(1.374)	(2.527)	(0.197)	(0.014)
BLOCK	0.005**	0.005***	0.005*	0.005*
	(2.200)	(2.827)	(1.802)	(1.770)
Ln(EQUITY)	-0.032***	-0.029***	-0.047***	-0.042***
	(-4.889)	(-3.534)	(-5.752)	(-4.220)
Ln(DEBT)	0.018***	0.016***	0.031 ***	0.029***
	(15.891)	(14.034)	(21.892)	(20.712)
$1/\sigma_E$	-0.121***	-0.136***	-0.108***	-0.118***
	(-10.274)	(-8.107)	(-7.268)	(-5.882)
EX_RET	-0.007***	-0.006*	-0.016 ***	-0.017***
	(-2.836)	(-1.883)	(-5.132)	(-2.838)
ROA	0.003	0.003	-0.016**	-0.014***
	(0.536)	(0.973)	(-2.098)	(-2.712)
Fixed effects	None	GICS	None	GICS
No. of obs.	884	884	884	884
R^2	40.82%	45.36%	52.53%	54.52%
Adjusted R^2	40.14%	44.10%	51.98%	53.47%

Table XX

Difference-in-Differences Estimators of Underlying Mechanisms in the Study of Firm Default Risk

This table reports the difference-in-differences estimator of variables related to stock liquidity, information efficiency, corporate governance, and financial constraints, respectively, based on the matched sample from the difference-in-differences test in Table XVII where the removal of the ten-second rule in 2009 is adopted as an exogenous shock to dark trading activities. Variables related to stock liquidity include quoted bid-ask spread (*SPREAD*) and proportion of days with zero returns (*ZERORET*) and both of them decreases with liquidity. *SPREAD* is calculated as the absolute difference between best bid and ask price divided by the mid-point of the best bid and ask price. *SPREAD* decreases with stock liquidity and is an illiquidity measure. *ZERORET* is calculated as the number of the days with zero returns divided by the total number of trading days over the fiscal year. Variables related to information efficiency include price delay measure (*DELAY*) and absolute stock return autocorrelation (*AUTOCOR*) and both of them proxies for information inefficiency. *DELAY* is measured by using 1 minus the ratio of R^2 with restrictions over R^2 without restrictions. The unrestricted R^2 is the R-squared obtained from regressing daily stock return on the concurrent market index return and lagged market returns up to 4 days. The restricted R^2 is the R-squared obtained from regressing daily stock return on the concurrent market index return only. *AUTOCOR* is the absolute value of autocorrelation in stock daily returns. Variables of corporate governance include blockholder ownership (*BLOCKO*) and number of blockholders (*NBLOCK*). *BLOCKO* measures aggregate percentage ownership of blockholders who hold at least 5% of total common shares outstanding. *NBLOCK* is number of blockholders who hold at least 5% of total common shares outstanding. Variable of financial constraints (*SA)* is calculated following Equation (9), and a larger *SA* represents higher financial constraints. Following Table XVII, we rank all sample firms based on their changes in dark trades surrounding the rule removal, and select the top 45% of the firms as treatment group and the bottom 45% of the firms as control group. We then run a probit model with the dependent variable being a dummy variable that is set to one for the firm in the treatment group and 0 in the control group. Propensity scores are used as predicted probabilities to match firms in two groups by closest propensity score match. This table reports the average variables in treatment group and control group in the year before event year (i.e., in year 2008) and the year after event year (i.e., in year 2010), respectively. It also reports difference-in-differences estimator of the variables based on the matched sample, as well as the corresponding t-statistics and p-values of the differences.

	Treatment		Control		Difference-in-differences	t-statistic	p-value
Variable	Before	After	Before	After			
SPREAD	0.032	0.035	0.031	0.021	0.012	4.185	0.000
ZERORET	0.190	0.234	0.169	0.179	0.034	2.648	0.009
DELAY	0.364	0.393	0.371	0.356	0.043	1.236	0.218
AUTOCOR	0.107	0.104	0.119	0.095	0.021	1.859	0.064
BLOCKO	25.067	17.632	27.014	11.785	7.794	2.583	0.010
NBLOCK	2.271	1.416	2.484	1.050	0.579	2.423	0.016
SA	0.572	0.500	0.612	0.831	-0.071	-0.197	0.845

Table XXI
Relative Importance of Underlying mechanisms in the Study of Firm Default Risk

This table reports the ordinary least squares (OLS) regressions results with standardized changes of variables based on the matched sample constructed in Table XVIII. The removal of the ten-second rule in 2009 is adopted as an exogenous shock to dark trading activities. Firm default risk is measured by one-year expected default frequency (*EDF_1y*) or five-year expected default frequency (*EDF_5y*). *ΔEDF_1y* (*ΔEDF_5y*) presents the change of *EDF_1y* (*EDF_5y*) from 2008 (pre-event year) to 2010 (post-event year). *ΔEDF_1y* (*ΔEDF_5y*) is then standardized by subtracting its mean value and dividing the difference by the standard deviation of *ΔEDF_1y* (*ΔEDF_5y*). *ΔEDF_1y* STD (*ΔEDF_5y* STD) denotes the standardized changes in *EDF_1y* (*EDF_5y*). The stock liquidity variables used are averaged quoted bid-ask spread (*SPREAD*) and proportion of days with zero returns (*ZERORET*). *ΔSPREAD* STD is the standardized changes in average value of quoted spread. *ΔZERORET* STD is the standardized changes in proportion of days with zero returns. The corporate governance variables are blockholder ownership (*BLOCKO*) and number of blockholders (*NBLOCK*). *ΔBLOCKO* STD represents the standardized changes in aggregate percentage ownership of blockholders. *ΔNBLOCK* STD stands for the standardized changes in number of blockowners. Similarly, the changes of block trading (*BLOCK*) and control variables are calculated and then standardized. Definitions of the variables are provided in Table III. t-statistics calculated based on heteroskedasticity-consistent standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Regressions of Standardized Changes in One-Year Expected Default Frequency				
	ΔEDF_1y STD			
	(1)	(2)	(3)	(4)
ΔBLOCKO STD	0.010		0.029	
	(0.278)		(0.768)	
ΔNBLOCK STD		0.031		0.043
		(0.843)		(1.165)
ΔSPREAD STD	-0.222***	-0.222***		
	(-4.883)	(-4.876)		
ΔZERORET STD			-0.197***	-0.197***
			(-4.960)	(-4.966)
ΔBLOCK STD	-0.003	-0.004	0.041	0.039
	(-0.068)	(-0.100)	(1.034)	(0.998)
ΔLn(EQUITY) STD	-0.638***	-0.637***	-0.601***	-0.601***
	(-12.299)	(-12.303)	(-12.321)	(-12.333)
ΔLn(DEBT) STD	0.085**	0.086**	0.059	0.058
	(2.285)	(2.295)	(1.548)	(1.529)
$\Delta 1/\sigma_E$ STD	-0.213***	-0.213***	-0.176***	-0.175***
	(-5.209)	(-5.217)	(-4.264)	(-4.252)
ΔEX_RET STD	0.000	0.000	-0.009	-0.009
	(0.002)	(0.011)	(-0.238)	(-0.228)
ΔQ STD	0.059	0.058	0.057	0.056
	(1.359)	(1.335)	(1.309)	(1.293)
ΔROA STD	-0.013	-0.013	-0.002	-0.002
	(-0.347)	(-0.342)	(-0.063)	(-0.057)
Fixed effects	None	None	None	None
No. of obs.	442	442	442	442
R^2	40.86%	40.95%	40.96%	41.06%
Adjusted R^2	39.63%	39.72%	39.73%	39.83%

Table XXI - *Continued*

Panel B: Regressions of Standardized Changes in Five-Year Expected Default Frequency				
	ΔEDF_5y STD			
	(1)	(2)	(3)	(4)
ΔBLOCKO STD	0.038		0.047	
	(0.886)		(1.098)	
ΔNBLOCK STD		0.070*		0.076*
		(1.660)		(1.792)
ΔSPREAD STD	-0.147***	-0.146***		
	(-2.819)	(-2.816)		
ΔZERORET STD			-0.095**	-0.095**
			(-2.046)	(-2.064)
ΔBLOCK STD	0.027	0.025	0.059	0.057
	(0.588)	(0.535)	(1.317)	(1.260)
ΔLn(EQUITY) STD	-0.365***	-0.364***	-0.313***	-0.313***
	(-6.160)	(-6.168)	(-5.563)	(-5.576)
ΔLn(DEBT) STD	0.214***	0.213***	0.207***	0.206***
	(5.009)	(5.014)	(4.754)	(4.743)
$\Delta 1/\sigma_E$ STD	-0.101**	-0.100**	-0.086*	-0.084*
	(-2.159)	(-2.148)	(-1.803)	(-1.782)
ΔEX_RET STD	-0.144***	-0.143***	-0.158***	-0.157***
	(-3.116)	(-3.107)	(-3.429)	(-3.421)
ΔQ STD	-0.029	-0.030	-0.036	-0.038
	(-0.579)	(-0.613)	(-0.728)	(-0.759)
ΔROA STD	-0.050	-0.049	-0.043	-0.043
	(-1.142)	(-1.135)	(-0.979)	(-0.971)
Fixed effects	None	None	None	None
No. of obs.	442	442	442	442
R^2	22.73%	23.08%	21.61%	21.97%
Adjusted R^2	21.12%	21.48%	19.98%	20.35%

Table XXII

Residual Effect of Dark Trading on Firm Default Risk after Controlling for Possible Mechanisms

This table reports the regression results of difference-in-differences of firm default risk, measured by one-year expected default frequency (*EDF_1y*) or five-year expected default frequency (*EDF_5y*), after controlling for possible mechanisms based on the matched sample from the difference-in-differences test in Table XVII where the removal of the ten-second rule in 2009 is adopted as an exogenous shock to dark trading activities. In Panels A and B, we control for possible mechanisms of stock liquidity, information efficiency, and blockholder ownership. In Panels C and D, the mechanism of firm value is further controlled with firm value measured by Tobin's Q (*Q*). Variables related to stock liquidity include quoted bid-ask spread (*SPREAD*) and proportion of days with zero returns (*ZERORET*) and both of them decreases with liquidity. *SPREAD* is calculated as the absolute difference between best bid and ask price divided by the mid-point of the best bid and ask price. *SPREAD* decreases with stock liquidity and is an illiquidity measure. *ZERORET* is calculated as the number of the days with zero returns divided by the total number of trading days over the fiscal year. Variables related to information efficiency include price delay measure (*DELAY*) and absolute stock return autocorrelation (*AUTOCOR*) and both of them proxies for information inefficiency. *DELAY* is measured by using 1 minus the ratio of R^2 with restrictions over R^2 without restrictions. The unrestricted R^2 is the R-squared obtained from regressing daily stock return on the concurrent market index return and lagged market returns up to 4 days. The restricted R^2 is the R-squared obtained from regressing daily stock return on the concurrent market index return only. *AUTOCOR* is the absolute value of autocorrelation in stock daily returns. Variables of corporate governance include blockholder ownership (*BLOCKO*) and number of blockholders (*NBLOCK*). *BLOCKO* measures aggregate percentage ownership of blockholders who hold at least 5% of total common shares outstanding. *NBLOCK* is number of blockholders who hold at least 5% of total common shares outstanding. Following Table XVII, we rank all sample firms based on their changes in dark trades surrounding the rule removal, and select the top 45% of the firms as treatment group and the bottom 45% of the firms as control group. We then run a probit model with the dependent variable being a dummy variable that is set to one for the firm in the treatment group and 0 in the control group. Propensity scores are used as predicted probabilities to match firms in two groups by closest propensity score match. This table reports the regression results based on the matched sample of the year before and the year after the exogenous event. *TREAT* is a dummy variable equal to one if a stock is in the treatment group and zero if in the control group. *AFTER* is a dummy variable equal to one for 2010 (post-event year) and zero for 2008 (pre-event year). *TREAT×AFTER* is the interaction between these two variables. Industry fixed effects are constructed based on 2-digit GICS code (GICS). t-statistics calculated based on heteroskedasticity-consistent standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table XXII - *Continued*

Panel A: Regressions of EDF_1y									
	EDF_1y								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
TREAT×AFTER	0.169***	0.156***	0.160***	0.164***	0.168***	0.168***	0.172***	0.176***	0.180***
	(4.417)	(4.061)	(4.174)	(4.278)	(4.395)	(4.379)	(4.483)	(4.522)	(4.645)
TREAT	-0.128***	-0.128***	-0.130***	-0.137***	-0.139***	-0.123***	-0.125***	-0.135***	-0.137***
	(-3.795)	(-3.828)	(-3.878)	(-4.135)	(-4.185)	(-3.660)	(-3.719)	(-3.997)	(-4.064)
AFTER	-0.279***	-0.270***	-0.279***	-0.280***	-0.290***	-0.275***	-0.285***	-0.292***	-0.303***
	(-9.289)	(-8.648)	(-8.901)	(-9.024)	(-9.320)	(-8.987)	(-9.241)	(-9.409)	(-9.782)
SPREAD		0.768**	0.736**	1.302***	1.254***				
		(2.437)	(2.314)	(6.171)	(5.744)				
ZERORET						-0.161	-0.158	0.078	0.070
						(-1.534)	(-1.514)	(1.007)	(0.908)
DELAY		0.063	0.058			0.149***	0.141***		
		(1.490)	(1.364)			(3.176)	(2.961)		
AUTOCOR				-0.557***	-0.557***			-0.403***	-0.407***
				(-4.796)	(-4.802)			(-3.279)	(-3.327)
BLOCKO		0.000		0.000		0.000		-0.000	
		(0.170)		(0.028)		(0.018)		(-0.429)	
NBLOCK			-0.006		-0.006		-0.007		-0.009**
			(-1.210)		(-1.365)		(-1.397)		(-1.975)
Fixed effects	GICS	GICS	GICS	GICS	GICS	GICS	GICS	GICS	GICS
No. of obs.	884	884	884	884	884	884	884	884	884
R^2	19.30%	21.13%	21.26%	22.90%	23.08%	20.65%	20.84%	20.41%	20.78%
Adjusted R^2	18.10%	19.67%	19.81%	21.48%	21.66%	19.19%	19.38%	18.95%	19.32%

Table XXII - *Continued*

Panel B: Regressions of EDF_5y									
	EDF_5y								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
TREAT×AFTER	0.199***	0.188***	0.188***	0.192***	0.193***	0.199***	0.199***	0.202***	0.203***
	(3.932)	(3.669)	(3.695)	(3.743)	(3.776)	(3.885)	(3.910)	(3.923)	(3.964)
TREAT	-0.091**	-0.090**	-0.090**	-0.095**	-0.095**	-0.084**	-0.084**	-0.091**	-0.091**
	(-2.251)	(-2.223)	(-2.221)	(-2.348)	(-2.349)	(-2.066)	(-2.065)	(-2.239)	(-2.248)
AFTER	-0.478***	-0.466***	-0.466***	-0.471***	-0.471***	-0.467***	-0.468***	-0.476***	-0.479***
	(-14.077)	(-13.080)	(-13.022)	(-13.164)	(-13.171)	(-13.202)	(-13.136)	(-13.325)	(-13.4048)
SPREAD		0.529*	0.527*	0.818***	0.820***				
		(1.842)	(1.826)	(3.219)	(3.205)				
ZERORET						-0.237**	-0.236**	-0.064	-0.063
						(-2.093)	(-2.076)	(-0.682)	(-0.670)
DELAY		0.040	0.041			0.131**	0.131**		
		(0.759)	(0.779)			(2.284)	(2.263)		
AUTOCOR				-0.274*	-0.276*			-0.131	-0.134
				(-1.724)	(-1.738)			(-0.815)	(-0.836)
BLOCKO		0.000		0.000		0.000		0.000	
		(0.882)		(0.823)		(0.843)		(0.595)	
NBLOCK			0.004		0.004		0.004		0.001
			(0.677)		(0.604)		(0.591)		(0.231)
Fixed effects	GICS	GICS	GICS	GICS	GICS	GICS	GICS	GICS	GICS
No. of obs.	884	884	884	884	884	884	884	884	884
R^2	19.30%	21.13%	21.26%	22.90%	23.08%	20.65%	20.84%	20.41%	20.78%
Adjusted R^2	18.10%	19.67%	19.81%	21.48%	21.66%	19.19%	19.38%	18.95%	19.32%

Table XXII - *Continued*

Panel C: Regressions of EDF_1y with Q Controlled									
	EDF_1y								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
TREAT×AFTER	0.150***	0.139***	0.143***	0.146***	0.150***	0.150***	0.154***	0.158***	0.163***
	(4.008)	(3.697)	(3.810)	(3.909)	(4.022)	(4.008)	(4.111)	(4.167)	(4.287)
TREAT	-0.117***	-0.118***	-0.119***	-0.127***	-0.128***	-0.111***	-0.113***	-0.124***	-0.125***
	(-3.541)	(-3.592)	(-3.642)	(-3.897)	(-3.946)	(-3.383)	(-3.442)	(-3.735)	(-3.800)
AFTER	-0.272***	-0.264***	-0.273***	-0.274***	-0.284***	-0.268***	-0.278***	-0.285***	-0.297***
	(-9.278)	(-8.664)	(-8.935)	(-9.065)	(-9.377)	(-8.998)	(-9.268)	(-9.459)	(-9.855)
Q	-0.024***	-0.024***	-0.024***	-0.025***	-0.025***	-0.025***	-0.025***	-0.025***	-0.025 ***
	(-3.198)	(-3.296)	(-3.334)	(-3.196)	(-3.233)	(-3.167)	(-3.207)	(-3.051)	(-3.094)
SPREAD		0.759**	0.726**	1.287***	1.237***				
		(2.297)	(2.175)	(5.690)	(5.282)				
ZERORET						-0.189*	-0.187*	0.053	0.044
						(-1.726)	(-1.713)	(0.652)	(0.545)
DELAY		0.058	0.053			0.151***	0.143***		
		(1.388)	(1.254)			(3.248)	(3.024)		
AUTOCOR				-0.571***	-0.571***			-0.409***	-0.413***
				(-4.841)	(-4.846)			(-3.285)	(-3.332)
BLOCKO		0.000		-0.000		-0.000		-0.000	
		(0.031)		(-0.117)		(-0.119)		(-0.577)	
NBLOCK			-0.007		-0.007		-0.007		-0.010**
			(-1.398)		(-1.550)		(-1.582)		(-2.173)
Fixed effects	GICS	GICS	GICS	GICS	GICS	GICS	GICS	GICS	GICS
No. of obs.	884	884	884	884	884	884	884	884	884
R^2	20.94%	22.67%	22.85%	24.58%	24.80%	22.34%	22.57%	22.09%	22.52%
Adjusted R^2	19.67%	21.15%	21.33%	23.10%	23.32%	20.81%	21.05%	20.56%	21.00%

Table XXII - *Continued*

Panel D: Regressions of EDF_5y with Q Controlled									
	EDF_5y								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
TREAT×AFTER	0.164***	0.154***	0.155***	0.158***	0.159***	0.164***	0.165***	0.168***	0.170***
	(3.321)	(3.105)	(3.134)	(3.183)	(3.215)	(3.328)	(3.355)	(3.377)	(3.420)
TREAT	-0.070*	-0.070*	-0.070*	-0.075*	-0.075*	-0.062	-0.062	-0.069*	-0.069**
	(-1.796)	(-1.787)	(-1.788)	(-1.916)	(-1.919)	(-1.577)	(-1.580)	(-1.768)	(-1.779)
AFTER	-0.464***	-0.454***	-0.455***	-0.460***	-0.461***	-0.454***	-0.456***	-0.464***	-0.467***
	(-14.020)	(-13.103)	(-13.056)	(-13.222)	(-13.234)	(-13.224)	(-13.163)	(-13.354)	(-13.446)
Q	-0.047***	-0.046***	-0.046***	-0.047***	-0.047***	-0.048***	-0.048***	-0.048***	-0.048***
	(-3.757)	(-3.783)	(-3.787)	(-3.755)	(-3.760)	(-3.695)	(-3.701)	(-3.646)	(-3.654)
SPREAD		0.511	0.507	0.790***	0.788***				
		(1.636)	(1.616)	(2.880)	(2.851)				
ZERORET						-0.292**	-0.290**	-0.111	-0.112
						(-2.433)	(-2.420)	(-1.125)	(-1.127)
DELAY		0.031	0.032			0.135**	0.134**		
		(0.606)	(0.614)			(2.409)	(2.372)		
AUTOCOR				-0.300*	-0.301*			-0.141	-0.144
				(-1.873)	(-1.884)			(-0.875)	(-0.893)
BLOCKO		0.000		0.000		0.000		0.000	
		(0.695)		(0.635)		(0.667)		(0.400)	
NBLOCK			0.003		0.002		0.002		-0.000
			(0.448)		(0.384)		(0.368)		(-0.021)
Fixed effects	GICS	GICS	GICS	GICS	GICS	GICS	GICS	GICS	GICS
No. of obs.	884	884	884	884	884	884	884	884	884
R^2	30.63%	31.00%	30.98%	31.27%	31.25%	31.38%	31.36%	30.89%	30.88%
Adjusted R^2	29.52%	29.65%	29.62%	29.92%	29.90%	30.03%	30.01%	29.53%	29.52%

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