

The Effect of “Black Swan” Events on Stock Markets Liquidity and CDS Markets

P. Joakim Westerholm Zixiu Zhao *

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Abstract

In this article, we investigate the impact of unforeseen “black swan” events, on the interplay between stock and CDS markets, in the context of COVID-19 pandemic. Our findings highlight a marked decline in stock market efficiency and subsequent erosion of liquidity as a result of the onset of the pandemic. Notably, the traditional perspective of CDS markets playing a secondary role to stock markets is challenged during this period. We observe a dynamic, bidirectional information exchange between the two markets. Furthermore, in the wake of such “black swan” events, the CDS market emerges as a pivotal player in the price discovery process for stock markets.

Keywords: Liquidity, stock, credit default swap, black swan events, COVID-19, price discovery

JEL Codes: G10, G11, G12, G13, G14, G15

*P. Joakim Westerholm (corresponding author) is from H69 Business School Building, Cnr Codrington and Rose Sts, Darlington NSW Australia 2008; joakim.westerholm@sydney.edu.au. Zixiu Zhao is also from H69 Business School Building, Cnr Codrington and Rose Sts, Darlington NSW Australia 2008; steve.zhao@sydney.edu.au.

1 Introduction

Do “black swan” events¹ impact information transmission between equity markets and other securities markets? These events typically emerge a few times per decade, yet their impact is profound and widespread. Occurrences such as the 2008 financial crisis and the 2010 flash crash highlight the unforeseeable characteristics and considerable impacts associated with such “black swan” events. In the past few years, a devastating global health crisis, named COVID-19, engulfed the globe with unprecedented spread. It was first announced as an impending storm by the Wellcome Trust in late January. However, it was not until months later that the World Health Organization officially recognized this imminent global crisis. Following the information, the COVID-19 pandemic sparked a massive spike in uncertainty and the financial turbulence reached a zenith that the world hadn’t experienced since the days of the Great Depression. (Baker et al., 2020). It is reasonable to consider the pandemic as a “black swan” event, which has never occurred before and differs from previous financial crises with several unique characteristics that cause the failure of existing risk pricing models. (Yarovaya et al., 2020)

Under the effect of this “black swan” event, the VIX reached over 80, while Nasdaq Composite indices took a dramatic 12 percent dive, indicating an unprecedented decline in the security market. Whether there is a shortage of liquidity or whether there is information inefficiency becomes a major concern among both academics and policymakers. In the real economy, the availability of bank capital does not serve as a restrictive factor for lending activities. As elaborated by Li et al. (2020), it is evidenced that the aggregate deposit inflows during the crisis sufficiently met the escalated demand for liquidity. This surplus efficiently facilitated the banks’ lending capabilities, illustrating that the magnitude of banks’ pre-crisis deposit base does not exhibit a direct correlation with their lending capacities across various banks. Thus, this demonstrates the role of banks as crucial liquidity providers

¹The black swan event is defined as a high-impact event that is difficult to predict and is unavoidable. It is mostly treated as an exogenous shock on the financial system.(Investopedia, 2022)

during times of crisis, such as the COVID-19 pandemic. In the context of the securities market, O'Hara and Zhou (2021) postulate that a liquidity deficit emerges in the corporate bond market during periods of crisis. They further assert that interventions implemented by the Federal Reserve increase the liquidity provision, ultimately returning it to the pre-crisis level. Correspondingly, a similar liquidity scarcity has been identified through the lens of bubble activities during crisis periods (Narayan, 2020). This phenomenon has been elucidated through the analysis of retail trading activities in stock markets (Ozik et al., 2021). They primarily emphasize the role of governmental intervention, which typically trails the initial reactions of financial markets. However, this literature does not provide a comprehensive understanding of the direct impact of crisis information and the corresponding response of financial markets in the context of COVID-19. Therefore, our primary objective is to investigate how liquidity and direct information transmission changed under the effect of COVID-19, particularly within the stock market.

To provide a complete picture of the liquidity and information transmission mechanisms we include the credit default swap (CDS) market in our analysis. CDS contracts are derivative contracts that facilitate investors to trade credit risk. They act as hedging tools for investors to manage the risk within their investment portfolio. Simultaneously, they incorporate the information in financial markets, resulting in the price discovery function of this specific derivative market. These two benefits bring the CDS market into the focus of research in information transmission mechanisms under the effect of the “black swan” event. As there is remarkable volatility in the stock market during Covid-19, the CDS market, concurrently, experienced an extraordinary escalation in trading activity with an exceptional \$4.6 (Zoltan Fekete, 2020) trillion dollar surge in March alone. The literature presents a complex relationship between equity markets and CDS markets.

From one perspective, plenty of research suggests a leading role for the CDS market in the price discovery process. Longstaff et al. (2003) and Marsh and Wagner (2016) find the predictability of CDS markets on the return of the US equity stock market. Focusing on the

information transmission mechanism, investors take advantage of CDS markets to use CDS contracts as a channel for insider trading and are believed to create an information inflow from CDS markets to equity markets, especially under the effect of negative credit news (Acharya & Johnson, 2007). It is consistent with Berndt and Ostrovnaya (2014), indicating that a strong spillover effect from CDS markets to equity markets corresponds to negative earning news. To analyze the efficiency of this mechanism, Amadori et al. (2014) elucidate that CDS markets can predict several financial markets including equity markets and option markets, and act as a leader in the information transmission process. In recent years, Kryzanowski et al. (2017) postulate that the CDS markets often precede and direct the movements in stock markets. This is primarily attributed to the superior information processing capabilities of the participants within CDS markets, enabling enhanced price discovery in response to macroeconomic news, and thereby, creating a competitive edge over equity markets.

Contrastingly, Hilscher et al. (2015) recently argue that the CDS market is a sideshow and they provide evidence that the information flow from equity markets to CDS markets instead of vice versa. They claim that CDS market participants may hedge to comply with investment policy and make the information not to be accurately and immediately reflected in their CDS spreads. Consistently, Wang et al. (2023) provide evidence for the same result that equity markets play a significantly leading role in the information transmission between them and CDS markets. To be more specific, Kiesel et al. (2016) find a 2-day predictability of equity markets on CDS markets, and CDS markets do not generate a great impact on equity markets.

This complex picture of the lead-lag relation between equity and CDS markets provides plenty of room for us to look at the effect of the “black swan” event on such kind of relationship. Boehmer et al. (2015) demonstrate that the emergence of single-name credit default swap contracts can lead to a decline in equity market quality, precipitated by liquidity shortages and subsequent pricing inefficiencies. Adding to this intricacy, Wang et al.

(2023) analyze firm-level data from 2001 to 2017 to indicate that there is limited evidence for the effect of the financial crisis on the information transmission mechanism between equity markets and CDS markets and they find the bidirectional flow of information between those two markets. Thus, it seems that the CDS markets are not a sideshow anymore, especially in recent years and a conspicuous gap emerges in the current literature, highlighting a deficiency in understanding the impact of “black swan” events such as the COVID-19 pandemic on the information transmission between equity and CDS markets.

Our analysis extends the literature related to “black swan” events, particularly COVID-19, and provides insight into how the uncertainty due to such events affects the liquidity in equity markets and the information transmission between equity and CDS markets. We report three important findings. First, the liquidity of stock markets decreases due to the outbreak of COVID-19. The results are consistent with the application of measures constructed from different perspectives. Second, information transmission between equity and CDS markets is not unidirectional anymore, which means that CDS markets are no longer a sideshow of the equity market during the “black swan” periods. There is a bidirectional flow of information between those two markets under the effect of COVID-19. Third, the escalation of activities in CDS markets decreases the liquidity of equity markets. During COVID-19, CDS markets provide a way for investors to hedge the credit risk of stocks which deter participants in stock markets, leading to a deterioration of equity markets,

This paper is organized as follows: Section 2 describes data and variables construction. The empirical methodologies and results are presented in Section 3. Robustness tests are shown in Section 4. Section 5 concludes.

2 Data Description

2.1 Sample Construction

We use data from three data sources. We begin with all S&P 500 firms from the Center for Research in Security Prices (CRSP). Data for daily transactions of relevant stocks are collected from Jan 1st, 2019 to Dec 31st, 2020. Bid-ask spread, effective spread, realized spread, price impact, and SDD5² are calculated by the data from Refinitiv.

CDS data are obtained from Markit. We focus on the daily transaction data of single-name CDS for S&P 500 firms from Jan 1st, 2019 to Dec 31st, 2020.

2.2 Variable Construction

2.2.1 Liquidity Measures

The liquidity estimator is selected from different perspectives.

a. Quoted spread To capture the transaction costs, the quoted spread (bid-ask spread) is a common way to measure liquidity in the stock market. Bid-ask spreads reflect the asymmetric information costs and order execution costs and may capture both explicit and implicit transaction costs. It is calculated by the difference between the bid and ask price divided by the midpoint between two prices, which is defined in Equation 1.

$$Quotedspread_{i,t} = \frac{(Ask_{i,t} - Bid_{i,t})}{m_{i,t}} \quad (1)$$

b. Effective spread Considering the depth of the stock market, the effective spread is applied to describe the total depth of the market and to measure the illiquidity in the equity market. (Boehmer, 2005) It is defined in Equation 2, where q represents the trade direction (1 for buyer and -1 for seller), $P(i, t)$ is the transaction price for individual stocks, and $m(i, t)$

² SDD5 is a measure constructed by Della Vedova et al. (2021) to describe the depth of the limit order book. It is used as an alternative liquidity measure in this paper.

is defined by the midpoint between bid and ask prices.

$$Effectivespread_{i,t} = 2 \times q \times \frac{(P_{i,t} - m_{i,t})}{m_{i,t}} \quad (2)$$

c. Price impact From the perspective of price base, Amihud (2002) introduces the illiquidity ratio which is commonly used in the analysis of the price impact of trading. It is easy to implement in the stock market with daily data and captures the time effect of the illiquidity in the equity market (Equation 3). The logarithm of such liquidity measured is applied in this paper to represent the percentage change of liquidity. Based on the invariance theory, Kyle and Obizhaeva (2016) introduce a liquidity index that does not depend on time units (Equation 4), which is defined by $\sigma(R^2)$, the volatility of squared return, divided by the dollar volume of individual stock. A more general estimate, price impact, is applied to measure the informational orders. It is defined in Equation 5, where q represents the trade direction (1 for buyer and -1 for seller), $m(i, t)$ is defined by the midpoint between bid and ask prices, and $m(i, t + 5)$ is the midpoint 5 minutes later for individual stocks.

$$AmihudIlliquidityRatio_{i,t} = \frac{1}{N} \sum_{i=1}^N \frac{|R_i|}{Dollarvolume_i} \quad (3)$$

$$KyleLiquidityIndex_{i,t} = \left(\frac{\sigma_{R_i}^2}{Dollarvolume_{i,t}} \right)^{\frac{1}{3}} \quad (4)$$

$$Priceimpact_{i,t} = 2 \times q \times \frac{(m_{i,t+5} - m_{i,t})}{m_{i,t}} \quad (5)$$

d. Depth of markets Scaled Depth Difference (SDD) constructed by Della Vedova et al. (2021) and Birru (2015) examines the relative level of asymmetry in the order book at a

particular point in time (Equation 6). SDD_5 is selected in this paper to represent the depth of the limit order book and as an alternative for liquidity measures.

$$SDD_{i,t,x} = \frac{(QuoteAsk_{i,t,x} - QuoteBid_{i,t,x})}{(QuoteAsk_{i,t,x} + QuoteBid_{i,t,x})} \quad (6)$$

where $QuoteAsk_{i,t,x}$ and $QuoteBid_{i,t,x}$ are the respective ask and bid quotes at depth level x in stock i at time t . 5 is selected for x in this paper to represent the depth of the limit order book and as an alternative for liquidity measures.

2.2.2 Explanatory Variables

a. Event indicator To identify a relevant event indicator, recent literature presents several choices for the separation point of the sample period: first, the announcement of institutions about COVID-19. On January 31, 2020, the Wellcome Trust announced one of the first earliest warnings for investors about the coming effect of COVID-19; second, the change point of effective spread based on different industries. For instance, focusing on the retail industry, Ozik et al. (2021) take 16 March as the beginning of the lockdown period; third, the structural change point in volatility for stock markets. Baek et al. (2020) use the Markov Switching regime AR (1) model introduced in Hamilton and Hamilton and Susmel (1994) to identify the point, 24th February 2020, which is the shift point of the volatility in the US stock market. Given that financial markets may not instantaneously respond to warning announcements, defining the COVID-19 financial period based on such notifications presents significant challenges. Moreover, relying on the lagged inflection point in the effective spread across industries as a signal of changing financial market conditions does not necessarily offer an insightful representation of the precise moment the markets entered the COVID-19 crisis phase. Consequently, we choose the third approach that integrates more detailed information into the state transitions of dynamic financial markets. This method is designed to provide a more precise delineation of the transition points between different

financial states. We construct a dummy variable, *Crisis*, to represent “black swan” events, which equals 1 when financial markets are in the “black swan” period. Following Hamilton and Susmel (1994), we get the separation point of COVID-19 February 24th, 2020 from the Markov Switching Regime model, which is presented in Figure 1. VIX data used in the Markov Switching Regime model are collected from the Federal Reserve Bank of St. Louis.

b. CDS markets CDS spreads are commonly used in previous studies to analyze the effect of different factors on the performance of CDS markets. Due to difficulties such as the lack of time series data on actual transaction prices, Berndt and Obreja (2010) conduct the estimator of CDS return by the rate of return on the riskless bond plus the change in the value of the CDS contract divided by par. To obtain a deep insight into the price in CDS markets, Qiu and Yu (2012) focus on the CDS premium obtained by the daily composite five-year CDS premium in basis points. Since single-name and index CDS contracts may have different responses to the financial crisis and effect on stock markets, the CDS factor can be categorized in this way. We simply use single-name CDS spread to construct security markets-related variable, CDS.

c. Equity market control variables We control for overall stock market trading activities with two variables. First, *Volatility* is the idiosyncratic volatility of each stock in our sample, defined as the deviation of the stock price from mid-price within one day. Second, *Volume* is the natural log of the total daily trading dollar volume of each stock.

2.3 Descriptive Statistics

Descriptive statistics for all liquidity measures and dependent variables are reported in Table 1. There are 488 firms in the base model analysis while 485 firms are selected for extended analysis during COVID-19. Panel A of Table 1 presents the summary statistics for liquidity measures. The average quoted spread is around 8.63 bps and the average effective spread is 5 bps. The average price impact for our sample is 5.11 bps.

Panel B of Table 1 reports summary statistics for CDS markets and other control variables. The mean logarithm of the CDS spread is -5.05 and the average volatility and volume are -4.49 and 14.62 respectively.

3 Result

3.1 Base result

We estimate the base model as follows:

$$L_{i,t} = \beta_1 Crisis_{i,t} + \beta_2 X_{i,t-1} + \mu_s + \varepsilon_{i,t} \quad (7)$$

where the dependent variable $L(i, t)$ describes the liquidity of the stock i on the day t , estimated by different approaches in Section 3. $Crisis(i, t)$ is a dummy variable that equals one if the transaction date (t) is after February 24th, 2020, which is obtained by Markov Switching regime AR (1) introduced by Hamilton and Susmel (1994). $X(i, t - 1)$ represents a set of stock controls for stock i on day $t-1$, including the idiosyncratic daily volatility, the log of the number of the daily trading volume. We include μ_s to control for the stock fixed effects as the stock time-unvarying characteristics have been proven to play an important role in determining the liquidity of the stock under the effect of COVID-19. Standard errors are clustered at stock levels.

Table 2 presents the results of the base model for each of the six market liquidity measures. The primary observation is that the results indicate that, all else constant, stock markets experience a significant increase in illiquidity during COVID-19. The estimated coefficients on the Crisis are positive and significant in all regressions. It elucidates that COVID-19 negatively affects stock markets, leading to a deterioration of the liquidity in stock markets. For example, the estimated coefficient of 0.000239 on Crisis in the quoted spread regression indicates that under the effect of COVID-19, the quoted spread increases by 2.39 bps (this

represents approximately 27.7% of the mean quoted spread of 8.63 bps). Similarly, the outbreak of COVID-19 boosts the effective spread by 1.41bps (nearly 28.2% of the mean effective spread of 5bps). For those companies under the impact of COVID-19, the price impact is intensified by 1.11 bps (approximately 21.7% of the mean price impact of 5.11). In the context of the Amihud illiquidity ratio and Kyle liquidity index, positive coefficients on the Crisis claim that the outbreak of COVID-19 increases illiquidity in the stock market and all the results are significant at 0.1% significance level. Analogously, the findings derived from SDD5 provide supporting evidence that the pandemic increases the degree of information asymmetry in stock markets, which leads to a reduction in the liquidity of stock markets.

Results for the other control variables are as follows. Enhanced overall trading activities are associated with increases in the liquidity of stock markets. As the estimated coefficients on the volatility of stocks suggest, augmented risk levels in stocks are negatively associated with the liquidity of stock markets. This can be rationalized by the fact that volatile markets tend to deter traders, particularly liquidity traders.

To summarize, COVID-19 leads to a deterioration of stock markets, resulting in a significant drop in liquidity. This drastic drop is further examined through the activity in the CDS market in the following subsections.

3.2 The predictability of CDS markets on equity markets

Following Hilscher et al. (2015), the pooled vector autoregression (VAR) is examined for equity returns and credit protection returns.

$$Z_{i,t} = \alpha + \sum_1^k \beta_k Z_{i,t-k} + \varepsilon_{i,t} \quad (8)$$

where $Z = \{R_{CDS}, R_S\}$ is a set of two main variables: CDS daily return and stock daily return, calculated by the percentage change of CDS spread and stock price. Based on the selection criteria BIC, AIC, and HQIC, the optimal lag term k is selected as 4. The Granger

test is passed for two variables.

Table 3 presents estimated results of the VAR model across the whole sample period with a lag term of 4. Figure 2 plots internal responses of two variables with daily frequency. The first panel presents sensitivities of CDS returns to lagged CDS returns (left) and lagged equity returns (right), moving from lags of 1 to 10. It indicates that there is a lead-lag relation within CDS return series, while such relation between CDS returns and equity returns is negatively significant within 3 days. This is consistent with previous literature that stock markets can predict CDS markets. The second panel draws a picture of the sensitivities of equity returns to lagged equity returns (right) and lagged CDS returns (left). It highlights that equity returns can be affected by the CDS returns at least two days ago. With 3 and 4 lags, CDS markets continue to play a significant role in the price discovery process with equity markets.

Table 6 presents the fraction of forecast-error variance explained by exogenous shocks to two return variables defined in Equation 8: R_S and R_{CDS} . It demonstrates that future returns of stock markets are significantly influenced, 7.9% of forecast-error variance, by shocks to CDS returns, whereas shocks to R_S only contribute 0.5% to the forecast-error variance of R_{CDS} . Thus, during COVID-19, there is a bidirectional adjustment between CDS markets and equity markets. Instead of stock markets moving ahead and affecting CDS markets, CDS markets are not a sideshow for equity markets anymore and play a dominant information transmission role between these two markets.

Furthermore, we follow Wang et al. (2023) to divide the full sample period into two subperiods: pre-”black swan” period (January 1st, 2019 to December 31st, 2019) and the ”black swan” period (January 1st, 2020 to December 31st, 2020). The Granger test of two variables is passed within two subperiod.

Table 4 presents estimated results of the VAR model across the whole sample period with a lag term of 8. Figure 3 plots internal responses of two markets with daily frequency during the pre-”black swan” period. The first panel presents the sensitivity of CDS returns

to lagged CDS returns (left) and lagged equity returns (right), moving from lags of 1 to 10, indicating that there is a leading role of equity markets on the lead-lag relation between CDS and equity markets. This result is in alignment with the result of Hilscher et al. (2015). The second panel presents responses of equity returns to lagged equity returns (right) and lagged CDS returns (left). Different from previous literature, it provides limited evidence that CDS returns can affect equity returns with 2 and 6 lags. This result is supported by Wang et al. (2023) that while equity returns lead to CDS returns after the 2008 financial crisis, the speed of adjustment of the CDS market to equity markets has increased during this period.

Table 5 presents estimated results of the VAR model across the whole sample period with a lag term of 8. Figure 4 draws internal responses of two markets with daily frequency during the "black swan" period. The first panel presents the sensitivity of CDS returns to lagged CDS returns (left) and lagged equity returns (right), moving from lags of 1 to 10, while the second panel shows responses of equity returns to lagged equity returns (right) and lagged CDS returns (left). It elucidates a bidirectional flow of information between these markets and CDS returns significantly affect equity returns during the crisis period which is consistent with benchmark VAR model analysis in this section that CDS markets play an important role in the lead-lag relation between two markets. The lag term selection of 4, compared with 8 in the pre-"black swan" period, also shows the increasing speed of reaction of financial markets to information during the "black swan" period.

The last two panels in Table 6 show the fraction of forecast-error variance explained by exogenous shocks to two return variables during two sub-periods: the pre-"black swan" period and the "black swan" period.

In conclusion, the speed of adjustment of the CDS market to equity markets increases due to the effect of the 2008 financial crisis and finally results in a bidirectional flow of information between those two markets because of the outbreak of COVID-19. "Black swan" events change the information transmission mechanism between two markets and locate the

price discovery function of CDS markets so that the information flow from CDS markets to equity markets assumes an increasingly pronounced significance, particularly during the “black event” period.

3.3 Information transmission role of CDS markets

To broaden the scope of our analysis and deepen our understanding of the subject matter, we incorporate the examination of the Credit Default Swap (CDS) market into our base model:

$$L_{i,t} = \beta_1 Crisis_{i,t} + \beta_2 CDS_{i,t-1} + \beta_3 X_{i,t-1} + \mu_s + \varepsilon_{i,t} \quad (9)$$

where the dependent variable $L_{i,t}$ describes the liquidity of the stock i on the day t , estimated by different measures in Section 3. CDS captures the daily return of single-name CDS contract i on the day t . Crisis is a dummy variable that equals one if the transaction date (t) is after Feb 24. $X_{i,t-1}$ represents a set of stock controls for stock i on day $t-1$, including the idiosyncratic daily volatility, the log of the number of the daily trading volume. We include μ_s to control for the stock fixed effects as the stock time-unvarying characteristics have been proven to play an important role in determining the liquidity of the stock under the effect of COVID-19. Standard errors are clustered at stock levels.

Table 7 presents results for each of the six market liquidity measures. The most important observation is that, all else constant, there is a significantly negative relation between CDS spread and the liquidity of stock markets during COVID-19. The estimated coefficients on Crisis are positive and are consistent with the results of our base model, which demonstrate that the outbreak of COVID-19 deteriorates stock markets by inducing a decline in the liquidity of equity markets.

CDS results from Equation 9 in Table 7 draw a more detailed picture of the information transmission mechanism. Positive estimated coefficients on CDS presented in Table 7 for

each liquidity measure (except for SDD5) indicate that liquidity of stock markets decreases as the CDS spread widens. The estimated coefficient of 0.000142 on the CDS variable in the quoted spread regression indicates that under the effect of COVID-19, the quoted spread increases by 0.142 bps (this represents approximately 1.65% of the mean quoted spread of 8.63 bps) as CDS spreads increase 10 percentage. Similarly, the 10% change in CDS spread boosts the effective spread by 0.0814 bps (nearly 1.63% of the mean effective spread of 5bps). For those companies under the impact of COVID-19, the price impact is intensified by 1.04 bps (approximately 2.03% of the mean price impact of 5.106) while the CDS spread widens 10 percent. The other price impact indicators, Amihud illiquidity ratio and Kyle liquidity index also increase with a broadening of CDS spreads during the "black swan" period. In addition, the coefficient on SDD5 is not statistically significant, potentially because of insufficient data on equities associated with CDS contracts. Then after the interaction term of CDS spread and COVID-19 indicator is added to the regression model, estimates coefficients are the same as predicted in Table 7. During the COVID-19 pandemic, the escalation in CDS spreads resulted in the expansion of both quoted and effective spreads. This phenomenon exacerbated information asymmetry within stock markets, consequently leading to a decline in market liquidity. This effect is more pronounced in stocks with higher credit risk. Based on credit spreads, we categorize stocks into two groups: the highest 10% credit spread group and the lowest 10% credit spread group. After sorting the stocks whose group classification remained consistent throughout the sample period, Table 8 and Table 9 present the model results, offering deeper insights into the impact of COVID-19 on information transmission between CDS markets and stock markets. Our findings indicate that the negative relationship between stock market liquidity and CDS spreads is intensified during the COVID-19 period, particularly for stocks with higher credit risk. This is evidenced by the significantly positive coefficient for the interaction term between CDS spreads and the event indicator in the highest 10% credit spread group, while no such effect is observed in the lowest 10% group.

In the face of "black swan" events, credit risk escalates across the financial environment.

On the one hand, CDS markets are treated as a risk mitigation tool for portfolio hedging. Some institutional investors will trade CDS to implement their hedging strategies, such as delta hedging strategies, in stock markets. Market makers will take this activity when setting the price in stock markets. Due to the outbreak of “black swan” events, these hedging activities externally decrease the liquidity of stock markets as they generate trades that are in the same direction of order flow. On the other hand, if the hedging channel is the only channel for information transmission between two markets, price impact indicators will not decrease as shown in the results, due to the lack of information content in this channel. Positive coefficients on price impact indicate that the increase in CDS spread will diminish price efficiency in stock markets. This can be rationalized by the trader-driven information spillover, examined by Boehmer et al. (2015). Informed traders use CDS markets and stock markets as two alternative venues to trade on private information or credit risk. Increasing credit risk attracts those traders to CDS markets and improves the price efficiency in CDS markets. Such trading activities deter investors from stock markets, leading to a lagged reaction of equity markets and deterioration of liquidity in stock markets. The results for the other control variables are as follows. In consistent with our previous analysis, during COVID-19, intense overall trading activities and considerable volatility make stock markets less attractive to traders and thus increase the illiquidity of stock markets. In summary, we believe that the CDS market acts as a hedging tool and a private information trading venue during the “black swan” period, particularly the COVID-19 period, leading to or at least preceding the decrease in liquidity of the stock market.

To shed light on this mechanism, we investigate the role of CDS markets on the activities of institutions in stock markets during the “black swan” period. Institutional activity is defined by trading volume, which is more than 20k or 50k, over total trading volume. The logarithm of institutional trading volume is added to the regression model to test the mediating effect.

First, we add the 20k institutional trading activity to the regression model 9. Table 10

shows results for each of the six market liquidity measures. The estimated coefficient of institutional trading is significantly negative for all liquidity measures except for SDD5, indicating that there is a strongly negative relationship between institutional trading behavior and liquidity in the stock market. Since SDD5 describes the relative level of asymmetry in the order book, more institutional trading activities should lead to an increase in SDD5, which is evidenced by the positive result in the table. During COVID-19, we observe a drastic drop in institutional trading activity, which is consistent with the result of Boehmer et al. (2015). It shows that the trader spillover effect cannot explain well the information transmission mechanism between the CDS market and the stock market during COVID-19. Table 11 presents similar results as we change from 20k institutional trading to 50k institutional trading.

Then Sobel’s (1982) test of mediation is applied to test whether institutional trading serves as a channel for the information transmission between CDS markets and stock markets during COVID-19. The result is shown in the bottom line of Table 10 and 11. The results of the mediation analysis provide evidence that the behavior of institutions acts as a mediator in the information transmission between the CDS market and the stock market. The significant T-statistic from Sobel’s test indicates that institutions respond to the effect of COVID-19, which is the increase in the credit risk in financial markets, represented by the CDS spread and move from stock markets to CDS markets. Finally, they take the liquidity from stock markets to CDS markets in a short period to hedge their position and speculate based on their information.

3.4 Industry

To present a more comprehensive analysis of the dynamic relationship between Credit Default Swap (CDS) markets and equity markets, we investigate the effect of the COVID-19 pandemic on the informational environment across various sectors. Our sample encompasses ten distinct industries: basic materials, consumer goods, consumer services, energy, finan-

cials, healthcare, industrials, technology, telecommunications services, and utilities. The results of our analysis are displayed in Table 12 to Table 21.

Consistent with previous results, we find that the outbreak of COVID-19 precipitated a significant decline in stock market liquidity across all ten sectors. Moreover, a pronounced negative correlation between CDS spreads and stock market liquidity is evident in our findings, as reflected in Table 12 and Table 15. However, a notable exception arises in the basic materials and energy sectors, where the interaction term between the COVID-19 event indicator and CDS spreads is significantly positive. This result implies that the pandemic has exacerbated the negative relationship between CDS spreads and stock market liquidity specifically within these two industries. In other words, the CDS market assumes a more pronounced role in the pricing dynamics of these sectors during the pandemic-induced crisis period.

The observed sector-specific outcomes can be attributed to the distinct characteristics of the COVID-19 pandemic and the corresponding policy interventions implemented by governments worldwide. The imposition of lockdown measures, designed to curtail the spread of the virus, led to severe restrictions on mobility and a substantial decline in energy demand. Consequently, energy production was significantly scaled back, as evidenced by the marked reduction in output from nuclear power plants in both Europe and the United States during the first quarter of 2020. Simultaneously, global demand for natural gas experienced a contraction of approximately 2%, with the steepest declines observed in China, Europe, and the United States. This disruption in the supply-demand equilibrium within the basic materials and energy sectors amplified credit risk, thereby widening CDS spreads for firms operating within these industries.

In summary, the increased prominence of CDS spreads in the basic materials and energy sectors during the pandemic highlights the critical role of credit markets in assessing firm-level risk amid systemic shocks. The widening of CDS spreads in these sectors reflects heightened market perceptions of default risk, driven by both demand-side and supply-side

disruptions induced by the pandemic.

In summary, the heightened prominence of CDS spreads in the basic materials and energy sectors during the pandemic underscores the critical role of credit markets in assessing firm-level risk amid systemic shocks. The escalation in credit risk contributes to a decrease in stock market liquidity, as investors become more risk-averse and less willing to trade equities of firms with elevated default probabilities. Consequently, the interplay between CDS spreads and liquidity is exacerbated due to the outbreak of COVID-19, reinforcing the interdependence of credit and equity markets during crisis periods.

4 Robustness test

In this section, we further conduct the same analysis of the 2008 financial crisis and the 2010 flash crash, which are believed to be other “black swan” events. The shocking point is selected based on the collapse of Lehman Brothers, Sep 15th, 2008, and the occurrence of the flash crash, May 6th, 2010. We sample from Jan 1st, 2007 to Dec 31st, 2009 to cover the persistence of the effect of the financial crisis, while the period from Jan 1st, 2010 to Sep 31st, 2010 is selected due to the rapid occurrence and the ambiguous nature of the impact.

Table 22 and Table 23 report descriptive statistics for all liquidity measures and dependent variables in the analysis of the 2008 financial crisis and the 2010 flash crash. 52703 daily observations are used in the analysis of the 2010 flash crash and 131408 daily observations are collected for the 2008 financial crisis. The average quoted spread is 7.54 bps during the 2008 financial crisis and 4.69 bps across the 2010 flash crash. The average effective spread also reaches a high level, 5.61 bps for the 2008 financial crisis and 4.24 bps for the 2010 flash crash. The mean price impact is 4.49 bps under the effect of the 2008 financial crisis and 4.17 bps due to the outbreak of the 2010 flash crash.

Panel B of Table 22 and Table 23 show that the mean CDS spread is at a high level during two periods, -4.43 for the 2008 financial crisis and -4.59 for the 2010 flash crash.

4.1 2008 financial crisis

Table 24 reports the estimated results from our VAR model in the case of the 2008 financial crisis. Figure 5 plots the internal responses of two variables with daily frequency. The first row presents sensitivities of CDS returns to lagged CDS returns (left) and lagged equity returns (right), moving from lags of 1 to 10, while the second row draws the picture of the sensitivities of equity returns to lagged equity returns (right) and lagged CDS returns (left). It indicates that the lead-lag relation between CDS markets and stock markets is not clear enough and CDS return will not significantly affect stock return most of the time. However, it provides limited evidence that the speed of information adjustment on the CDS market increases during the financial crisis, which is consistent with Wang et al. (2023). Table 25 presents the fraction of forecast-error variance explained by exogenous shocks to two return variables defined in Equation 8: R_{CDS} and R_S . Shocks to R_S only contribute 0.5% to the forecast-error variance of R_{CDS} , while only 0.7% of the forecast-error variance of R_S are explained by shocks to R_{CDS} . However, there is limited evidence that there is bidirectional information flow between these two markets and stock markets are not in the leading stage of lead-lag relation between the two markets. More interestingly, the explanatory power of R_{CDS} decreases to 1% during the "black swan" period from 1.3% across pre- "black period". This can be rationalized by the fact that the CDS market, as one of the main sources triggering the 2008 financial crisis, led to panic among investors. The decline in the utilization of CDS contracts and the enhancement of risk management within the CDS market decrease the CDS market activities and reduce the efficiency of the information transmission channel between the CDS market and the stock market

4.1.1 Relation between CDS markets and equity markets

Then we investigate the relationship between CDS markets and stock markets under the effect of the financial crisis. Table 26 and Table 27 present regression results for the same liquidity measures(except for SDD5) in our main analysis during the 2008 financial crisis.

Positive coefficients on the CDS indicator indicate that an increase in CDS spread significantly decreases liquidity in stock markets, which is consistent with our main analysis in the context of COVID-19. These results confirm the information transmission role of CDS markets during the “black event” period: in the face of “black swan” events, the uncertainty risk of firms increases drastically to a high level. Institutional traders will include CDS in their portfolio to hedge the overall risk, while informational traders are attracted by CDS markets and will speculate in CDS markets to increase the trading activities in such markets. As a result, the liquidity of stock markets decreases and CDS markets play a more important price discovery role in the information transmission mechanism between these two markets during “black swan” periods.

We also run Sobel’s test to figure out whether institutional trading behavior decreases the liquidity of the stock market. The significant T-statistic in Table 28 and Table 29 confirm the mediator role of the institution, indicating that in response to the financial crisis, institutions bring liquidity from stock markets to CDS markets in a short period either to hedge their position or speculate based on the information they have.

4.2 2010 flash crash

VAR estimation for the linkage between CDS and Stock markets during the 2010 flash crash is presented in Table 30. Figure 6 plots the internal responses of two variables with daily frequency.

Although the lead-lag relation is not clear, there is evidence that stock markets are more sensitive to the change in CDS markets, which is consistent with what happened after the 2008 financial crisis, evidenced by the previous 2008 financial crisis analysis. The fraction of forecast-error variance in Table 35 indicates that shocks to R_S only contribute 0.3% to the forecast-error variance of R_{CDS} , while during the crisis period, it increases to 0.7%. In contrast, 0.8% of the forecast-error variance of R_S is explained by shocks to R_{CDS} in the whole period analysis. This ratio increases from 0.5% to 1% across the pre “black swan”

period and “black swan” period. These results confirm the bidirectional information flow between two markets and CDS is more likely acting as a leading role in this relationship.

4.2.1 Relation between CDS markets and equity markets

Then we analyze the relationship between CDS markets and stock markets under the effect of the flash crash in 2010. Table 31 and Table 32 show regression results for the same liquidity measures (except for SDD5) in our main analysis during the 2010 flash crash. It elucidates that the liquidity shrinks due to the outbreak of the 2010 flash crash and an increase in CDS spread also significantly increases the illiquidity in stock markets. Positive coefficients on the interaction term between CDS spread and event indicator present that widened CDS spread significantly decreases the liquidity during the 2010 flash crash, which is consistent with our main results. Results of other control variables explain the same relationships as what we have in the main analysis.

Sobel’s test of the mediation is also conducted to draw a more detailed picture of the mechanism behind those two markets. The results are shown in Table 33 and Table 34, indicating that institutions bring liquidity from equity markets to CDS markets under the effect of the 2010 flash crash.

In summary, during the “black swan” period, credit risk across financial markets increases, leading to increases in hedging activities and credit risk speculating activities. The CDS market as one of the main markets providing an environment for these activities, deters informed investors, such as institutional investors, from stock markets, resulting in a decrease in the liquidity of equity markets.

5 Conclusion

We investigate the effect of the “black swan” event, which is COVID-19 in our analysis, on the liquidity of stock markets and event-direct information transmission between stock markets

and CDS markets. Due to the outbreak of COVID-19, stock markets become less efficient and there is a deterioration of liquidity, evidenced by the analysis of different perspectives of liquidity. Simultaneously, a bidirectional flow of information between CDS markets and equity markets elucidates that the CDS market is not a sideshow anymore and exacerbates or at least precedes the deterioration of equity markets with reduced liquidity. The information flow is further intensified by the black swan event of COVID-19, particularly for stocks with high credit risk, and for companies in the basic materials and energy sectors.

We conduct robustness tests for another two “black swan” events, which are the 2008 financial crisis and the 2010 flash crash. Results indicate that the shock of “black swan” events changes the information environment and transmission mechanism for financial markets, particularly in CDS and stock markets. It is consistent with our main analysis that uncertainty induced by “black swan” events will increase credit risk across financial markets and investors are deterred from stock markets and trade in CDS markets, leading to a deterioration of stock markets.

Table 1: Descriptive Statistics

Table 1 presents descriptive statistics for liquidity measurements (Panel A) and independent variables (Panel B) in the analysis of COVID-19.

	<u>Mean</u>	<u>25th Percentile</u>	<u>75th Percentile</u>	<u>Std. Dev</u>	<u>No. of Obs.</u>
<u>Panel A Liquidity Measurement</u>					
Quoted Spread	0.000863	0.0004397	0.0010241	0.0007737	227514
Effective Spread	0.0005012	0.000206	0.0005724	0.0006581	227514
Price Impact	0.0005111	0.0002459	0.0005911	0.0007295	227514
Amihud	-23.47471	-24.17481	-22.70711	1.172635	227514
Kyle Index	2.392143	0	3.642352	4.603044	227514
SDD5	0.0046538	-0.0493195	0.0590404	0.1304908	122773
<u>Panel B Independent Variables</u>					
Crisis	0.4334063	0	1	0.4955465	227514
CDS	-5.052537	-5.572765	-4.644859	0.7252723	93359
Volatility	-4.48814	-4.902963	-4.137586	0.5915344	227514
Volume	14.6232	13.85591	15.32694	1.15272	227514

Table 2: Base Result

Table 2 presents results from our base model on different liquidity measures: quoted spread, effective spread, price impact, Amihud illiquidity ratio, Kyle index, and SDD5. Regressions include stock fixed effects. Standard errors are clustered by firm. The t-statistics are reported in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	Quoted Spread	Effective Spread	Price Impact	Amihud	Kyle Index	SDD5
Crisis	2.680*** (0.120)	1.558*** (0.0723)	1.237*** (0.0763)	0.178*** (0.0138)	0.289*** (0.0214)	0.0243*** (0.00258)
Volatility	4.518*** (0.155)	2.110*** (0.0698)	2.088*** (0.0682)	0.753*** (0.00897)	1.280*** (0.0608)	0.00400** (0.00131)
Volume	-0.526*** (0.113)	-0.398*** (0.0680)	-0.293*** (0.0703)	-0.387*** (0.0117)	0.0473 (0.0444)	-0.00419* (0.00163)
Constant	35.44*** (2.121)	19.63*** (1.171)	18.23*** (1.189)	-14.52*** (0.204)	7.290*** (0.889)	0.0771** (0.0266)
Observations	227455	227455	227455	227455	227455	122742
Adj. R-squared	0.603	0.257	0.151	0.801	0.285	0.0175

Table 3: Vector Autoregression for CDS Returns and Stock Returns(Whole Sample Period)

Table 3 presents results from our VAR model across the whole sample period. R_{CDS} and R_S are two return variables defined in our VAR model, representing CDS return and Stock return. Based on the selection criteria BIC, AIC, and HQIC, the optimal lag term is selected as 4. The t-statistics are reported in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

		$\underline{R_{CDS}}$	$\underline{R_S}$
$\underline{R_{CDS}}$	t-1	0.072761*** (0.011051)	-0.007267 (0.004807)
	t-2	0.067785*** (0.011051)	-0.018996*** (0.004713)
	t-3	0.042411*** (0.009707)	-0.032286*** (0.006370)
	t-4	-0.018735* (0.009707)	0.010719* (0.005305)
$\underline{R_S}$	t-1	-0.095645*** (0.010395)	-0.042525*** (0.007778)
	t-2	-0.058213*** (0.009494)	-0.008518 (0.004713)
	t-3	-0.005157 (0.009388)	-0.045964*** (0.008021)
	t-4	0.011298 (0.010582)	-0.096030*** (0.007225)

Table 4: Vector Autoregression for CDS Returns and Stock Returns(Pre-”black swan” period)

Table 4 presents results from our VAR model during pre-”black swan” period. R_{CDS} and R_S are two return variables defined in our VAR model, representing CDS return and Stock return. Based on the selection criteria BIC, AIC, and HQIC, the optimal lag term is selected as 8. The t-statistics are reported in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

		<u>R_{CDS}</u>	<u>R_S</u>
<u>R_{CDS}</u>	t-1	0.008472 (0.014162)	0.013940*** (0.004020)
	t-2	0.077407*** (0.010221)	-0.023724*** (0.003401)
	t-3	0.033878*** (0.010014)	-0.003507 (0.003196)
	t-4	0.012945 (0.009787)	-0.000463 (0.003197)
	t-5	0.027667** (0.009120)	0.001114 (0.002995)
	t-6	-0.025628** (0.009420)	0.001744 (0.003116)
	t-7	-0.009565 (0.008559)	-0.012508*** (0.003328)
	t-8	0.029060** (0.009186)	-0.010368** (0.003464)
<u>R_S</u>	t-1	-0.117849*** (0.009682)	0.006769 (0.007079)
	t-2	-0.010411 (0.009072)	-0.030253*** (0.006487)
	t-3	0.005450 (0.009147)	-0.007465 (0.005989)
	t-4	-0.029834** (0.009092)	0.005266 (0.006061)
	t-5	0.020316* (0.008769)	-0.002964 (0.006570)
	t-6	0.008894 (0.008565)	-0.017187** (0.005797)
	t-7	-0.003304 (0.008460)	0.023225*** (0.005576)
	t-8	0.005868 (0.008822)	-0.006771 (0.005445)

Table 5: Vector Autoregression for CDS Returns and Stock Returns("black swan" period)

Table 5 presents results from our VAR model during the "black swan" period. R_{CDS} and R_S are two return variables defined in our VAR model, representing CDS return and Stock return. Based on the selection criteria BIC, AIC, and HQIC, the optimal lag term is selected as 4. The t-statistics are reported in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

		<u>R_{CDS}</u>	<u>R_S</u>
<u>R_{CDS}</u>	t-1	0.085240*** (0.018259)	-0.012496* (0.005595)
	t-2	0.064184*** (0.013124)	-0.017623** (0.005840)
	t-3	0.044821*** (0.012007)	-0.039214*** (0.008492)
	t-4	-0.025265** (0.008956)	0.013236* (0.006604)
<u>R_S</u>	t-1	-0.090838*** (0.012725)	-0.052712*** (0.009299)
	t-2	-0.067045*** (0.011330)	-0.005359 (0.008968)
	t-3	0.044821*** (0.011292)	-0.055239*** (0.009821)
	t-4	0.020865 (0.012776)	-0.118597*** (0.008758)

Table 6: Forecast Error Variance Decomposition

Table 6 reports the forecast error variance decomposition for our VAR model. R_{CDS} and R_S are two return variables defined in our VAR model, representing CDS return and Stock return. Sample periods are separated into two parts: the pre-”black swan” period and the ”black swan” period.

		Whole Sample Period									
Impulse Variable	Response Variable	1	2	3	4	5	6	7	8	9	10
R_{CDS}	R_{CDS}	100%	99.6%	99.5%	99.5%	99.5%	99.5%	99.5%	99.5%	99.5%	99.5%
	R_S	0	0.4%	0.5%	0.5%	0.5%	0.5%	0.5%	0.5%	0.5%	0.5%
R_S	R_{CDS}	7.6%	7.6%	7.7%	7.8%	7.9%	7.9%	7.9%	7.9%	7.9%	7.9%
	R_S	92.4%	92.4%	92.3%	92.2%	92.1%	92.1%	92.1%	92.1%	92.1%	92.1%
		”Black Swan” Period									
		1	2	3	4	5	6	7	8	9	10
R_{CDS}	R_{CDS}	100%	99.6%	99.5%	99.5%	99.5%	99.5%	99.5%	99.5%	99.5%	99.5%
	R_S	0	0.4%	0.5%	0.5%	0.5%	0.5%	0.5%	0.5%	0.5%	0.5%
R_S	R_{CDS}	7.6%	7.6%	7.7%	7.8%	7.9%	7.9%	7.9%	7.9%	7.9%	7.9%
	R_S	92.4%	92.4%	92.3%	92.2%	92.1%	92.1%	92.1%	92.1%	92.1%	92.1%
		Pre-”Black Swan” Period									
		1	2	3	4	5	6	7	8	9	10
R_{CDS}	R_{CDS}	100%	99.5%	99.5%	99.5%	99.4%	99.4%	99.4%	99.4%	99.4%	99.4%
	R_S	0	0.5%	0.5%	0.5%	0.6%	0.6%	0.6%	0.6%	0.6%	0.6%
R_S	R_{CDS}	6.9%	6.9%	7.0%	7.0%	7.0%	7.0%	7.0%	7.1%	7.1%	7.1%
	R_S	93.1%	93.1%	93%	93%	93%	93%	93%	92.9%	92.9%	92.9%

Table 7: CDS Result

Table 7 shows results of our extended model with interaction term (CDS \times Crisis) on different liquidity measures: quoted spread, effective spread, price impact, Amihud illiquidity ratio, Kyle liquidity index, and SDD5. Regressions include stock fixed effects. Standard errors are clustered by firm. The t-statistics are reported in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Quoted Spread	Quoted Spread	Effective Spread	Effective Spread	Price Impact	Price Impact	Amihud	Amihud	Kyle Index	Kyle Index	SDD5	SDD5
Crisis	1.983*** (0.172)	7.277** (2.318)	1.319*** (0.102)	4.160*** (1.047)	1.138*** (0.120)	2.817* (1.288)	0.180*** (0.0271)	0.336* (0.163)	0.183*** (0.0269)	1.090** (0.335)	0.0125*** (0.00354)	-0.0404 (0.0264)
CDS	0.954*** (0.285)	-0.0790 (0.489)	0.603*** (0.140)	0.0482 (0.223)	0.694** (0.222)	0.366 (0.271)	0.0946* (0.0428)	0.0641 (0.0386)	0.0635 (0.0718)	-0.113 (0.0729)	-0.00370 (0.00285)	0.00524 (0.00565)
Volatility	3.593*** (0.367)	3.624*** (0.366)	1.599*** (0.174)	1.616*** (0.174)	1.776*** (0.141)	1.786*** (0.144)	0.920*** (0.0246)	0.921*** (0.0247)	0.831*** (0.0899)	0.836*** (0.0905)	0.00250 (0.00166)	0.00221 (0.00169)
Volume	-0.604** (0.199)	-0.649** (0.208)	-0.283** (0.102)	-0.308** (0.108)	-0.425*** (0.110)	-0.439*** (0.115)	-0.528*** (0.0240)	-0.530*** (0.0241)	-0.00693 (0.0498)	-0.0146 (0.0515)	-0.00408* (0.00175)	-0.00375* (0.00169)
Crisis \times CDS		1.058* (0.451)		0.568** (0.203)		0.335 (0.250)		0.0313 (0.0312)		0.181** (0.0649)		-0.0103 (0.00531)
Observations	177010	177010	177010	177010	177010	177010	177010	177010	177010	177010	105068	105068
Adj. R-squared	0.623	0.626	0.321	0.322	0.323	0.324	0.686	0.686	0.196	0.196	0.0166	0.0171

Table 8: CDS Result-low Credit Risk

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Quoted Spread	Quoted Spread	Effective Spread	Effective Spread	Price Impact	Price Impact	Amihud	Amihud	Kyle Index	Kyle Index	SDD5	SDD5
Crisis	3.860*	-0.355	1.804**	3.396	0.993	-0.423	0.238*	-0.537	0.286*	-0.0425	0.0258*	-0.000678
	(1.605)	(6.768)	(0.565)	(1.681)	(0.678)	(3.666)	(0.0950)	(0.474)	(0.124)	(0.814)	(0.00870)	(0.0797)
CDS	0.274	1.210	0.442	0.0880	0.326	0.641	-0.0195	0.153	0.0964	0.169	-0.0299	-0.0257
	(0.793)	(1.679)	(0.399)	(0.731)	(0.347)	(0.975)	(0.0739)	(0.134)	(0.114)	(0.168)	(0.0196)	(0.0244)
Volatility	4.670**	4.526**	1.733*	1.787**	1.967*	1.919*	1.033***	1.007***	1.280***	1.269***	-0.00186	-0.00184
	(1.265)	(1.234)	(0.589)	(0.554)	(0.779)	(0.728)	(0.0681)	(0.0633)	(0.232)	(0.228)	(0.0115)	(0.0115)
Volume	-1.418	-1.301	-0.435	-0.480	-0.940	-0.901	-0.652***	-0.630***	-0.422***	-0.413***	0.00859	0.00865
	(0.712)	(0.686)	(0.766)	(0.741)	(0.550)	(0.463)	(0.0610)	(0.0583)	(0.0763)	(0.0629)	(0.0125)	(0.0126)
Crisis \times CDS		-1.209		0.457		-0.406		-0.222		-0.0942		-0.00733
		(1.859)		(0.507)		(1.193)		(0.149)		(0.259)		(0.0228)
Observations	10695	10695	10695	10695	10695	10695	10695	10695	10695	10695	3259	3259
Adj. R-squared	0.719	0.720	0.202	0.202	0.181	0.181	0.580	0.581	0.136	0.136	0.0129	0.0126

Table 9: CDS Result-High Credit Risk

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Quoted Spread	Quoted Spread	Effective Spread	Effective Spread	Price Impact	Price Impact	Amihud	Amihud	Kyle Index	Kyle Index	SDD5	SDD5
Crisis	2.665*** (0.378)	44.69*** (10.74)	1.581*** (0.204)	28.80*** (5.252)	1.351*** (0.196)	21.84*** (4.069)	0.200** (0.0530)	0.995 (0.816)	0.175 (0.0957)	5.124*** (0.827)	0.0536*** (0.0104)	-0.181 (0.212)
CDS	3.218** (0.795)	-0.0799 (0.709)	2.105*** (0.377)	-0.0312 (0.350)	1.751*** (0.244)	0.143 (0.333)	0.208** (0.0658)	0.145 (0.0840)	0.264 (0.146)	-0.124 (0.111)	0.0565** (0.0144)	0.0691** (0.0174)
Volatility	4.478*** (0.497)	4.202*** (0.516)	2.129*** (0.189)	1.949*** (0.215)	1.892*** (0.192)	1.757*** (0.216)	0.727*** (0.0321)	0.722*** (0.0327)	0.957*** (0.130)	0.924*** (0.132)	-0.00429 (0.00472)	-0.00286 (0.00525)
Volume	-0.391 (0.273)	-0.547 (0.257)	-0.288 (0.236)	-0.389 (0.228)	-0.276 (0.220)	-0.352 (0.213)	-0.374*** (0.0333)	-0.377*** (0.0344)	-0.0802 (0.0823)	-0.0986 (0.0813)	-0.00526 (0.00903)	-0.00483 (0.00926)
Crisis \times CDS		6.823** (1.692)		4.419*** (0.843)		3.325*** (0.654)		0.129 (0.133)		0.803*** (0.128)		-0.0380 (0.0338)
Observations	8335	8335	8335	8335	8335	8335	8335	8335	8335	8335	6280	6280
Adj. R-squared	0.542	0.561	0.358	0.380	0.351	0.367	0.747	0.748	0.179	0.182	0.0278	0.0284

Table 10: 20k Institutional trading behavior

Table 10 shows results of extended model with 20k institutional trading indicator during COVID-19. Sobel's test results are presented for different liquidity measures: quoted spread, effective spread, price impact, Amihud illiquidity ratio, Kyle liquidity index, and SDD5. The t-statistics are reported in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	(1)	(2)	(3)	(4)	(5)	(6)
	Quoted Spread	Effective Spread	Price Impact	Amihud	Kyle Index	SDD5
Institutional Trading (20K)	-6.458** (-2.63)	-2.011 (-1.66)	-2.107** (-2.67)	-1.278*** (-8.09)	-0.693 (-1.96)	0.0176 (0.81)
Crisis	1.980*** (11.31)	1.319*** (13.09)	1.138*** (9.70)	0.181*** (7.10)	0.183*** (6.65)	0.0124*** (3.53)
CDS	0.901** (3.23)	0.582*** (4.24)	0.674** (3.06)	0.0825* (2.02)	0.0547 (0.78)	-0.00340 (-1.20)
Volatility	3.532*** (9.82)	1.586*** (9.37)	1.759*** (12.79)	0.902*** (40.36)	0.823*** (9.42)	0.00275 (1.61)
Volume	-0.411* (-2.46)	-0.225* (-2.45)	-0.364*** (-3.50)	-0.489*** (-23.64)	0.0151 (0.35)	-0.00463* (-2.25)
Sobel's Test	-0.076***	-0.027***	0	0.029***	0.015***	0***
Observations	176350	176350	176350	176350	176350	104888
Adj. R-squared	0.624	0.323	0.327	0.684	0.217	0.017

Table 11: 50k Institutional trading behavior

Table 11 shows results of extended model with 50k institutional trading indicator during COVID-19. Sobel's test results are presented for different liquidity measures: quoted spread, effective spread, price impact, Amihud illiquidity ratio, Kyle liquidity index, and SDD5. The t-statistics are reported in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	(1)	(2)	(3)	(4)	(5)	(6)
	Quoted Spread	Effective Spread	Price Impact	Amihud	Kyle Index	SDD5
Institutional Trading (50K)	-5.659 (-1.64)	-1.968 (-1.05)	-2.519* (-2.46)	-1.494*** (-6.07)	-0.556 (-1.13)	-0.00824 (-0.32)
Crisis	1.969*** (11.62)	1.316*** (13.22)	1.133*** (9.70)	0.178*** (7.06)	0.182*** (6.72)	0.0124*** (3.52)
CDS	0.910** (3.22)	0.583*** (4.24)	0.671** (3.03)	0.0813 (1.91)	0.0561 (0.79)	-0.00369 (-1.27)
Volatility	3.551*** (10.03)	1.589*** (9.39)	1.757*** (12.64)	0.902*** (40.21)	0.826*** (9.57)	0.00247 (1.41)
Volume	-0.437** (-2.81)	-0.227* (-2.44)	-0.352** (-3.26)	-0.483*** (-23.10)	0.0107 (0.26)	-0.00378 (-1.85)
Sobel's Test	0.064***	0.026***	0.003***	-0.02***	-0.009***	0*
Observations	176350	176350	176350	176350	176350	104888
Adj. R-squared	0.623	0.323	0.327	0.684	0.217	0.017

Table 12: CDS Result-Basic materials

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Quoted Spread	Quoted Spread	Effective Spread	Effective Spread	Price Impact	Price Impact	Amihud	Amihud	Kyle Index	Kyle Index	SDD5	SDD5
Crisis	3.448** (0.787)	19.87* (6.464)	1.915*** (0.382)	11.19** (3.372)	2.030*** (0.312)	11.74*** (2.343)	0.236*** (0.0525)	0.784 (0.896)	0.382*** (0.0756)	0.902 (0.670)	0.0246 (0.0142)	-0.0305 (0.0721)
CDS	4.475*** (0.894)	1.448 (1.416)	1.891** (0.435)	0.180 (0.741)	2.414*** (0.412)	0.623 (0.544)	0.323** (0.0861)	0.222 (0.141)	0.351** (0.108)	0.256 (0.191)	-0.0146 (0.0277)	-0.00827 (0.0285)
Volatility	3.791** (0.887)	3.720** (0.868)	1.648** (0.424)	1.608** (0.400)	1.966*** (0.308)	1.924*** (0.293)	0.968*** (0.113)	0.965*** (0.112)	0.680*** (0.0775)	0.677*** (0.0774)	0.00197 (0.00708)	0.00239 (0.00728)
Volume	-0.420* (0.170)	-0.0750 (0.377)	-0.131 (0.133)	0.0637 (0.133)	-0.0815 (0.0989)	0.122 (0.122)	-0.483*** (0.0724)	-0.472*** (0.0651)	0.150* (0.0663)	0.161* (0.0590)	0.000112 (0.00525)	-0.00109 (0.00470)
Crisis \times CDS		3.285* (1.199)		1.856* (0.639)		1.943*** (0.433)		0.110 (0.173)		0.104 (0.135)		-0.0111 (0.0153)
Observations	9478	9478	9478	9478	9478	9478	9478	9478	9478	9478	5786	5786
Adj. R-squared	0.536	0.551	0.532	0.554	0.493	0.517	0.544	0.544	0.103	0.103	0.0168	0.0170

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: CDS Result-Consumer Good

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Quoted Spread	Quoted Spread	Effective Spread	Effective Spread	Price Impact	Price Impact	Amihud	Amihud	Kyle Index	Kyle Index	SDD5	SDD5
Crisis	3.003*** (0.626)	26.43 (13.91)	1.710*** (0.275)	11.72** (3.859)	1.320*** (0.266)	9.803** (3.328)	0.113 (0.0570)	0.260 (0.333)	0.219* (0.0877)	1.376 (0.751)	0.00476 (0.00736)	-0.0283 (0.0505)
CDS	3.263*** (0.495)	-1.185 (2.636)	1.488*** (0.293)	-0.413 (0.752)	1.606*** (0.328)	-0.00418 (0.679)	0.259*** (0.0382)	0.231** (0.0641)	0.386* (0.160)	0.166 (0.172)	-0.00119 (0.00868)	0.00437 (0.0164)
Volatility	3.936*** (0.938)	3.954*** (0.919)	1.637*** (0.348)	1.645*** (0.337)	1.737*** (0.356)	1.743*** (0.351)	0.746*** (0.0376)	0.746*** (0.0377)	1.076*** (0.126)	1.076*** (0.125)	0.00387 (0.00380)	0.00365 (0.00379)
Volume	-0.887 (0.529)	-0.834 (0.504)	-0.465 (0.253)	-0.443 (0.247)	-0.391 (0.226)	-0.372 (0.224)	-0.420*** (0.0288)	-0.420*** (0.0288)	-0.00496 (0.0923)	-0.00238 (0.0924)	0.00345 (0.00587)	0.00390 (0.00564)
Crisis × CDS		4.720 (2.705)		2.018* (0.745)		1.709* (0.643)		0.0296 (0.0622)		0.233 (0.142)		-0.00660 (0.0105)
Observations	15583	15583	15583	15583	15583	15583	15583	15583	15583	15583	8611	8611
Adj. R-squared	0.732	0.747	0.378	0.389	0.360	0.369	0.812	0.812	0.158	0.158	0.0111	0.0111

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: CDS Result-Consumer Service

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Quoted Spread	Quoted Spread	Effective Spread	Effective Spread	Price Impact	Price Impact	Amihud	Amihud	Kyle Index	Kyle Index	SDD5	SDD5
Crisis	3.565** (1.092)	3.263 (5.722)	1.871*** (0.497)	4.071 (2.559)	1.353*** (0.262)	2.148 (2.253)	0.125** (0.0439)	0.776*** (0.173)	0.302** (0.0847)	1.278* (0.538)	0.0225** (0.00769)	-0.159** (0.0410)
CDS	1.883* (0.886)	1.935 (0.988)	1.060* (0.483)	0.684 (0.702)	1.398** (0.480)	1.262 (0.699)	0.236* (0.101)	0.125 (0.111)	0.220 (0.209)	0.0536 (0.234)	-0.000743 (0.00629)	0.0273** (0.00949)
Volatility	4.493*** (0.899)	4.492*** (0.894)	1.972*** (0.341)	1.977*** (0.337)	1.653*** (0.307)	1.655*** (0.305)	0.825*** (0.0623)	0.826*** (0.0657)	0.871*** (0.123)	0.874*** (0.123)	0.00892* (0.00356)	0.00785* (0.00327)
Volume	-2.141* (0.788)	-2.139* (0.790)	-0.965** (0.277)	-0.982** (0.271)	-0.604** (0.174)	-0.610*** (0.162)	-0.501*** (0.0613)	-0.507*** (0.0642)	0.0839 (0.0979)	0.0762 (0.101)	-0.0140* (0.00549)	-0.0112* (0.00476)
Crisis × CDS		-0.0639 (1.213)		0.465 (0.506)		0.168 (0.479)		0.138*** (0.0343)		0.206 (0.107)		-0.0356*** (0.00804)
Observations	16765	16765	16765	16765	16765	16765	16765	16765	16765	16765	7335	7335
Adj. R-squared	0.662	0.662	0.348	0.349	0.243	0.243	0.771	0.773	0.168	0.169	0.0183	0.0249

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: CDS Result-Energy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Quoted Spread	Quoted Spread	Effective Spread	Effective Spread	Price Impact	Price Impact	Amihud	Amihud	Kyle Index	Kyle Index	SDD5	SDD5
Crisis	2.277*** (0.295)	18.99** (4.940)	1.950*** (0.360)	10.69** (2.909)	2.333*** (0.454)	10.41* (3.555)	0.448*** (0.0561)	-0.385 (0.626)	0.247** (0.0604)	4.237* (1.616)	0.00698 (0.00744)	0.0748 (0.0552)
CDS	2.793** (0.763)	-0.515 (0.627)	1.650*** (0.314)	-0.0792 (0.461)	2.126*** (0.299)	0.527 (0.600)	0.122** (0.0364)	0.287** (0.0946)	0.424** (0.120)	-0.365 (0.316)	0.00291 (0.0141)	-0.00694 (0.0158)
Volatility	0.587 (0.447)	0.736 (0.445)	0.00149 (0.290)	0.0792 (0.281)	0.408 (0.287)	0.480 (0.285)	0.904*** (0.0751)	0.897*** (0.0703)	0.165 (0.209)	0.200 (0.210)	-0.00794 (0.00455)	-0.00755 (0.00410)
Volume	0.265 (0.349)	0.212 (0.266)	0.206 (0.242)	0.179 (0.232)	-0.0631 (0.293)	-0.0885 (0.293)	-0.527*** (0.0590)	-0.524*** (0.0547)	0.349* (0.151)	0.336* (0.142)	-0.00313* (0.00140)	-0.00319* (0.00136)
Crisis × CDS		3.411** (1.015)		1.783* (0.609)		1.648* (0.753)		-0.170 (0.125)		0.814* (0.333)		0.0148 (0.0115)
Observations	23408	23408	23408	23408	23408	23408	23408	23408	23408	23408	13234	13234
Adj. R-squared	0.657	0.680	0.605	0.619	0.655	0.663	0.527	0.527	0.334	0.337	0.0148	0.0159

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16: CDS Result-Financials

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Quoted Spread	Quoted Spread	Effective Spread	Effective Spread	Price Impact	Price Impact	Amihud	Amihud	Kyle Index	Kyle Index	SDD5	SDD5
Crisis	1.461*** (0.279)	6.560* (3.149)	0.938*** (0.173)	2.238 (2.102)	0.819*** (0.197)	0.471 (2.805)	0.278*** (0.0601)	0.431 (0.327)	0.234*** (0.0542)	1.661* (0.784)	0.00908 (0.00902)	-0.00590 (0.0436)
CDS	-0.404 (0.577)	-1.195 (0.810)	-0.00895 (0.277)	-0.211 (0.456)	0.443 (0.237)	0.497 (0.576)	0.129** (0.0477)	0.105 (0.0661)	0.0921 (0.181)	-0.129 (0.242)	-0.0111 (0.00822)	-0.00931 (0.0127)
Volatility	3.989*** (0.577)	3.939*** (0.576)	1.712*** (0.296)	1.699*** (0.293)	1.780*** (0.272)	1.784*** (0.258)	0.933*** (0.0314)	0.931*** (0.0325)	0.873*** (0.116)	0.859*** (0.117)	0.00275 (0.00389)	0.00285 (0.00384)
Volume	-0.199 (0.254)	-0.144 (0.224)	0.102 (0.262)	0.116 (0.245)	-0.108 (0.190)	-0.112 (0.171)	-0.514*** (0.0335)	-0.512*** (0.0340)	-0.0310 (0.0682)	-0.0158 (0.0645)	-0.000105 (0.00481)	-0.000242 (0.00488)
Crisis × CDS		1.028 (0.635)		0.262 (0.415)		-0.0702 (0.549)		0.0309 (0.0616)		0.288 (0.158)		-0.00291 (0.00857)
Observations	43955	43955	43955	43955	43955	43955	43955	43955	43955	43955	25718	25718
Adj. R-squared	0.540	0.543	0.279	0.279	0.296	0.296	0.668	0.668	0.224	0.226	0.0213	0.0213

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 17: CDS Result-Healthcare

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Quoted Spread	Quoted Spread	Effective Spread	Effective Spread	Price Impact	Price Impact	Amihud	Amihud	Kyle Index	Kyle Index	SDD5	SDD5
Crisis	2.121*** (0.300)	8.438 (5.004)	1.354*** (0.210)	5.771 (2.976)	1.102*** (0.230)	4.838 (2.698)	0.0181 (0.0361)	-0.677** (0.226)	0.123** (0.0376)	0.169 (0.663)	0.0328*** (0.00618)	0.121* (0.0500)
CDS	1.521 (0.755)	0.544 (0.752)	0.881* (0.339)	0.198 (0.545)	0.706* (0.290)	0.128 (0.500)	0.108* (0.0400)	0.216*** (0.0316)	0.00979 (0.0960)	0.00271 (0.123)	0.0195*** (0.00396)	0.00318 (0.0121)
Volatility	4.590*** (1.008)	4.603*** (1.001)	2.121*** (0.343)	2.130*** (0.343)	1.804*** (0.269)	1.812*** (0.269)	0.798*** (0.0559)	0.797*** (0.0570)	0.701*** (0.0841)	0.701*** (0.0840)	-0.00455 (0.00406)	-0.00471 (0.00402)
Volume	0.105 (0.403)	0.0947 (0.420)	-0.249 (0.178)	-0.256 (0.187)	-0.327 (0.168)	-0.333 (0.179)	-0.462*** (0.0503)	-0.461*** (0.0491)	0.0487 (0.0615)	0.0487 (0.0614)	0.00748 (0.00729)	0.00839 (0.00705)
Crisis × CDS		1.164 (0.922)		0.814 (0.547)		0.689 (0.499)		-0.128** (0.0413)		0.00844 (0.119)		0.0166 (0.0102)
Observations	11294	11294	11294	11294	11294	11294	11294	11294	11294	11294	6837	6837
Adj. R-squared	0.575	0.577	0.385	0.388	0.331	0.333	0.630	0.631	0.135	0.135	0.0179	0.0187

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 18: CDS Result-Industrials

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Quoted Spread	Quoted Spread	Effective Spread	Effective Spread	Price Impact	Price Impact	Amihud	Amihud	Kyle Index	Kyle Index	SDD5	SDD5
Crisis	2.108*** (0.388)	5.896* (2.542)	1.504*** (0.229)	4.921*** (1.172)	1.180*** (0.158)	3.138* (1.295)	0.0929** (0.0323)	-0.0473 (0.224)	0.138** (0.0481)	0.399 (0.471)	0.0101 (0.00874)	-0.100 (0.0696)
CDS	0.370 (0.476)	-0.454 (0.695)	0.331 (0.232)	-0.412 (0.290)	0.0785 (0.194)	-0.347 (0.210)	0.0126 (0.0497)	0.0431 (0.0660)	-0.0321 (0.0580)	-0.0887 (0.100)	-0.00274 (0.00554)	0.0178 (0.0126)
Volatility	4.361*** (0.526)	4.430*** (0.498)	1.944*** (0.248)	2.007*** (0.231)	2.172*** (0.174)	2.208*** (0.168)	0.937*** (0.0469)	0.934*** (0.0469)	0.899*** (0.110)	0.904*** (0.111)	0.00692* (0.00275)	0.00549 (0.00318)
Volume	-0.989*** (0.269)	-1.098*** (0.241)	-0.503** (0.151)	-0.601*** (0.157)	-0.710*** (0.190)	-0.766*** (0.185)	-0.576*** (0.0411)	-0.572*** (0.0404)	-0.181** (0.0577)	-0.189** (0.0579)	-0.00766* (0.00283)	-0.00524 (0.00303)
Crisis × CDS		0.731 (0.505)		0.659** (0.229)		0.378 (0.257)		-0.0270 (0.0436)		0.0502 (0.0896)		-0.0212 (0.0143)
Observations	32555	32555	32555	32555	32555	32555	32555	32555	32555	32555	23668	23668
Adj. R-squared	0.560	0.561	0.496	0.500	0.540	0.542	0.654	0.654	0.158	0.158	0.0187	0.0209

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 19: CDS Result-Telecommunications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Quoted Spread	Quoted Spread	Effective Spread	Effective Spread	Price Impact	Price Impact	Amihud	Amihud	Kyle Index	Kyle Index	SDD5	SDD5
Crisis	0.399 (.)	-6.003 (.)	0.422 (.)	2.174 (.)	0.217 (.)	1.243 (.)	0.0140 (.)	-0.256 (.)	0.0915 (.)	1.173 (.)	0 (.)	0 (.)
CDS	0.911 (.)	1.960 (.)	0.235 (.)	-0.0524 (.)	0.370 (.)	0.202 (.)	0.686 (.)	0.730 (.)	0.447 (.)	0.270 (.)	-0.145 (.)	-0.145 (.)
Volatility	0.0170 (.)	0.0468 (.)	0.0279 (.)	0.0197 (.)	0.346 (.)	0.342 (.)	0.547 (.)	0.548 (.)	0.210 (.)	0.205 (.)	0.0159 (.)	0.0159 (.)
Volume	0.147 (.)	0.154 (.)	0.0833 (.)	0.0812 (.)	-0.126 (.)	-0.127 (.)	-0.0375 (.)	-0.0372 (.)	0.252 (.)	0.250 (.)	-0.0445 (.)	-0.0445 (.)
Crisis × CDS		-1.360 (.)		0.372 (.)		0.218 (.)		-0.0573 (.)		0.230 (.)		0 (.)
Observations	985	985	985	985	985	985	985	985	985	985	491	491
Adj. R-squared	0.635	0.718	0.353	0.361	0.285	0.287	0.327	0.326	0.0937	0.0935	0.0777	0.0777

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 20: CDS Result-Technology

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Quoted Spread	Quoted Spread	Effective Spread	Effective Spread	Price Impact	Price Impact	Amihud	Amihud	Kyle Index	Kyle Index	SDD5	SDD5
Crisis	1.352** (0.457)	7.872 (5.096)	0.329 (0.247)	4.203 (3.062)	0.135 (0.315)	4.847 (3.253)	0.0399 (0.0740)	0.673 (0.719)	0.152* (0.0725)	1.739 (1.290)	-0.000884 (0.00429)	-0.0163 (0.0407)
CDS	1.533 (0.759)	0.731 (0.939)	0.318 (0.265)	-0.159 (0.432)	-0.109 (0.362)	-0.689 (0.458)	0.0432 (0.105)	-0.0346 (0.124)	0.129 (0.0722)	-0.0659 (0.169)	0.00649 (0.0113)	0.00869 (0.0166)
Volatility	2.113*** (0.487)	2.093*** (0.474)	1.458** (0.439)	1.446** (0.434)	1.460*** (0.250)	1.445*** (0.243)	0.806*** (0.0776)	0.804*** (0.0776)	0.839*** (0.157)	0.835*** (0.155)	-0.000569 (0.00295)	-0.000450 (0.00291)
Volume	-0.319 (0.187)	-0.195 (0.175)	-0.665* (0.303)	-0.591 (0.295)	-0.447* (0.193)	-0.357 (0.202)	-0.381*** (0.0536)	-0.369*** (0.0574)	0.0729 (0.0795)	0.103 (0.0766)	-0.00337 (0.00461)	-0.00353 (0.00494)
Crisis × CDS		1.322 (0.983)		0.786 (0.599)		0.956 (0.627)		0.128 (0.142)		0.322 (0.250)		-0.00311 (0.00854)
Observations	10187	10187	10187	10187	10187	10187	10187	10187	10187	10187	4044	4044
Adj. R-squared	0.684	0.689	0.164	0.165	0.136	0.138	0.771	0.772	0.163	0.164	0.00392	0.00371

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 21: CDS Result-Utilities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Quoted Spread	Quoted Spread	Effective Spread	Effective Spread	Price Impact	Price Impact	Amihud	Amihud	Kyle Index	Kyle Index	SDD5	SDD5
Crisis	1.284*** (0.271)	5.861 (4.841)	1.077*** (0.276)	0.295 (2.535)	1.068*** (0.244)	1.286 (2.174)	0.223*** (0.0296)	-0.157 (0.423)	0.173** (0.0556)	2.124** (0.662)	0.0170 (0.00993)	-0.0348 (0.0560)
CDS	0.698 (0.346)	-0.103 (0.903)	0.0517 (0.244)	0.188 (0.419)	0.600*** (0.150)	0.562 (0.339)	0.0639 (0.0447)	0.130 (0.0694)	0.244 (0.245)	-0.0972 (0.275)	-0.00344 (0.00678)	0.00462 (0.0139)
Volatility	3.709*** (0.498)	3.739*** (0.494)	1.834*** (0.234)	1.829*** (0.237)	1.830*** (0.192)	1.831*** (0.194)	0.864*** (0.0470)	0.862*** (0.0452)	1.064*** (0.122)	1.077*** (0.119)	0.00305 (0.00293)	0.00270 (0.00300)
Volume	-0.661** (0.227)	-0.660* (0.233)	-0.232 (0.193)	-0.233 (0.192)	-0.225 (0.172)	-0.225 (0.172)	-0.520*** (0.0702)	-0.520*** (0.0709)	-0.0694 (0.0940)	-0.0691 (0.0916)	-0.0158* (0.00561)	-0.0157* (0.00558)
Crisis × CDS		0.882 (0.936)		-0.151 (0.514)		0.0420 (0.436)		-0.0733 (0.0803)		0.376** (0.127)		-0.00980 (0.0120)
Observations	12800	12800	12800	12800	12800	12800	12800	12800	12800	12800	9344	9344
Adj. R-squared	0.531	0.534	0.222	0.222	0.220	0.220	0.584	0.584	0.153	0.155	0.0116	0.0118

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 22: Descriptive Statistics (2008 Financial Crisis)

Table 22 presents descriptive statistics for liquidity measurements (Panel A) and independent variables (Panel B) in the analysis of the 2008 financial crisis.

	<u>Mean</u>	<u>25th Percentile</u>	<u>75th Percentile</u>	<u>Std. Dev</u>	<u>No. of Obs.</u>
<u>Panel A Liquidity Measurement</u>					
Quoted Spread	0.0007545	0.0003783	0.0007526	0.0024259	133,998
Effective Spread	0.0005612	0.0003111	0.000611	0.0005607	133,998
Price Impact	0.000449	0.0001941	0.0005321	0.0005067	133,998
Amihud	-19.26858	-19.88622	-18.53581	1.063216	133,998
Kyle Index	10.3547	0	17.00372	11.62773	133,998
<u>Panel B Independent Variables</u>					
Crisis	0.6678085	0	1	0.471001	133,998
CDS	-4.425732	-5.128496	-3.801674	0.9205	131,408
Volatility	-4.050985	-4.508253	-3.6438	0.6512164	133,998
Volume	15.22205	14.47666	15.8653	1.065688	133,998

Table 23: Descriptive Statistics (2010 Flash Crash)

Table 23 presents descriptive statistics for liquidity measurements (Panel A) and independent variables (Panel B) in the analysis of the 2010 flash crash.

	<u>Mean</u>	<u>25th Percentile</u>	<u>75th Percentile</u>	<u>Std. Dev</u>	<u>No. of Obs.</u>
<u>Panel A Liquidity Measurement</u>					
Quoted Spread	0.0004689	0.0002942	0.0005236	0.0003259	53,739
Effective Spread	0.0004241	0.0002506	0.0004576	0.0008192	53,739
Price Impact	0.0004167	0.0002372	0.0004993	0.0005503	53,739
Amihud	-23.16237	-23.83538	-22.39111	1.117982	53,739
Kyle Index	2.479922	0	4.075256	2.777292	53,739
<u>Panel B Independent Variables</u>					
Crisis	0.5444463	0	1	0.4980252	53,739
CDS	-4.589081	-5.1728	-4.127064	0.7394085	52,703
Volatility	-4.501786	-4.864596	-4.166932	0.5333306	53,443
Volume	18.68229	18.00385	19.28351	0.999654	53,443

Table 24: Vector Autoregression for CDS Returns and Stock Returns(2008 Financial Crisis)

Table 24 presents results from our VAR model during the 2008 financial crisis. R_{CDS} and R_S are two return variables defined in our VAR model, representing CDS return and Stock return. Based on the selection criteria BIC, AIC, and HQIC, the optimal lag term is selected as 9. The t-statistics are reported in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

		R_{CDS}	R_S
R_{CDS}	t-1	0.040392*** (0.007493)	-0.000878 (0.003166)
	t-2	0.018906*** (0.004426)	0.003689 (0.002149)
	t-3	0.001459 (0.003338)	0.004625 (0.002459)
	t-4	0.006108* (0.002870)	-0.004174* (0.001992)
	t-5	0.003012 (0.002689)	0.003358 (0.001848)
	t-6	0.008642* (0.004228)	0.000375 (0.001967)
	t-7	0.001053 (0.002094)	0.000367 (0.001946)
	t-8	0.015299 (0.009788)	-0.001874 (0.001860)
	t-9	0.011712** (0.003620)	0.000768 (0.002790)
R_S	t-1	-0.076802 (0.043649)	-0.018242 (0.011543)
	t-2	-0.033275 (0.018376)	-0.026092* (0.010966)
	t-3	-0.013100 (0.008426)	-0.004290 (0.004897)
	t-4	-0.015585 (0.009906)	-0.009128* (0.004059)
	t-5	-0.017642 (0.009513)	-0.017113*** (0.003159)
	t-6	-0.007693 (0.004693)	0.019687*** (0.003748)
	t-7	-0.001119 (0.002884)	0.003466 (0.008032)
	t-8	-0.005935 (0.006419)	0.006263 (0.005223)
	t-9	-0.005486 (0.004006)	0.000349 (0.003224)

Table 25: Forecast error variance decomposition (2008 financial crisis)

Table 25 reports the forecast error variance decomposition for our VAR model during the 2008 financial crisis. R_{CDS} and R_S are two return variables defined in our VAR model, representing CDS return and Stock return.

2008 Financial Crisis											
Impulse Variable	Response Variable	1	2	3	4	5	6	7	8	9	10
R_{CDS}	R_{CDS}	100%	99.6%	99.5%	99.5%	99.5%	99.5%	99.5%	99.5%	99.5%	99.5%
	R_S	0	0.4%	0.5%	0.5%	0.5%	0.5%	0.5%	0.5%	0.5%	0.5%
R_S	R_{CDS}	0.7%	0.7%	0.7%	0.7%	0.7%	0.7%	0.7%	0.7%	0.7%	0.7%
	R_S	99.3%	99.3%	99.3%	99.3%	99.3%	99.3%	99.3%	99.3%	99.3%	99.3%
Pre "Black Swan" Period											
Impulse Variable	Response Variable	1	2	3	4	5	6	7	8	9	10
R_{CDS}	R_{CDS}	100%	99.3%	99.2%	99.2%	99.2%	99.2%	99.2%	99.2%	99.2%	99.1%
	R_S	0	0.7%	0.8%	0.8%	0.8%	0.8%	0.8%	0.8%	0.8%	0.9%
R_S	R_{CDS}	1.2%	1.2%	1.2%	1.2%	1.2%	1.3%	1.3%	1.3%	1.3%	1.3%
	R_S	98.8%	98.8%	98.8%	98.8%	98.8%	98.7%	98.7%	98.7%	98.7%	98.7%
"Black Swan" Period											
Impulse Variable	Response Variable	1	2	3	4	5	6	7	8	9	10
R_{CDS}	R_{CDS}	100%	99.3%	99.2%	99.2%	99.2%	99.2%	99.2%	99.2%	99.2%	99.1%
	R_S	0	0.7%	0.8%	0.8%	0.8%	0.8%	0.8%	0.8%	0.8%	0.9%
R_S	R_{CDS}	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%
	R_S	99%	99%	99%	99%	99%	99%	99%	99%	99%	99%

Table 26: CDS Results (2008 financial crisis)

Table 26 shows results of our extended model with interaction term (CDS \times Crisis) on different liquidity measures: quoted spread, effective spread, price impact, Amihud illiquidity ratio, and Kyle liquidity index during the 2008 financial crisis. Regressions include stock fixed effects. Standard errors are clustered by firm. The t-statistics are reported in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	(1)	(2)	(3)	(4)	(5)	(6)
	Quoted Spread	Quoted Spread	Effective Spread	Effective Spread	Price Impact	Price Impact
Crisis	0.000184*** (0.0000213)	0.00150*** (0.000211)	0.0000849*** (0.0000104)	0.00102*** (0.000172)	0.0000962*** (0.00000888)	0.000841*** (0.000123)
CDS	0.000362*** (0.0000394)	0.000122*** (0.0000357)	0.000217*** (0.0000394)	0.0000465 (0.0000243)	0.000191*** (0.0000267)	0.0000548** (0.0000209)
Crisis \times CDS		0.000283*** (0.0000427)		0.000201*** (0.0000361)		0.000160*** (0.0000256)
Volatility	0.000280*** (0.0000300)	0.000270*** (0.0000293)	0.000135*** (0.0000216)	0.000129*** (0.0000209)	0.000128*** (0.0000143)	0.000122*** (0.0000137)
Volume	-0.000292*** (0.0000430)	-0.000301*** (0.0000423)	-0.0000217 (0.0000331)	-0.0000282 (0.0000325)	-0.0000434 (0.0000221)	-0.0000486* (0.0000216)
Observations	131408	131408	131408	131408	131408	131408
Adj. R-squared	0.0449	0.0468	0.636	0.656	0.547	0.562

Table 27: CDS Result Continued (2008 Financial Crisis)

Table 27 shows remaining results of our extended model with interaction term (CDS \times Crisis) on different liquidity measures: quoted spread, effective spread, price impact, Amihud illiquidity ratio, and Kyle liquidity index during the 2008 financial crisis. Regressions include stock fixed effects. Standard errors are clustered by firm. The t-statistics are reported in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	(7)	(8)	(9)	(10)
	Amihud	Amihud	Kyle Index	Kyle Index
Indicator	-0.0206*	-0.0502	0.224*	1.815***
	(0.00819)	(0.0470)	(0.0879)	(0.417)
CDS	0.118***	0.124***	1.062***	0.771***
	(0.0105)	(0.0123)	(0.114)	(0.133)
Crisis \times CDS		-0.00638		0.343***
		(0.00990)		(0.0857)
Volatility	0.637***	0.637***	3.827***	3.815***
	(0.0107)	(0.0107)	(0.148)	(0.148)
Volume	-0.532***	-0.532***	-0.354**	-0.365**
	(0.0129)	(0.0128)	(0.133)	(0.133)
Observations	131408	131408	131408	131408
Adj. R-squared	0.804	0.804	0.114	0.114

Table 28: 20k Institutional trading behavior (2008 financial crisis)

Table 28 shows results of extended model with 20k institutional trading indicator during the 2008 financial crisis. Sobel's test results are presented for different liquidity measures: quoted spread, effective spread, price impact, Amihud illiquidity ratio, and Kyle liquidity index. The t-statistics are reported in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	(1)	(2)	(3)	(4)	(5)
	Quoted Spread	Effective Spread	Price Impact	Amihud	Kyle Index
Crisis	0.000207*** (8.80)	0.0000896*** (6.57)	0.0000917*** (8.80)	-0.0372*** (-4.27)	0.156 (1.73)
Institutional Trading (20k)	0.000772** (2.94)	0.000163 (0.74)	-0.000136 (-0.91)	-0.588*** (-6.16)	-2.177* (-2.05)
CDS	0.000378*** (9.81)	0.000219*** (5.61)	0.000187*** (7.01)	0.106*** (10.19)	1.019*** (8.39)
Volatility	0.000295*** (9.22)	0.000137*** (5.75)	0.000124*** (7.88)	0.624*** (58.45)	3.780*** (24.36)
Volume	-0.000315*** (-6.87)	-0.0000231 (-0.64)	-0.0000374 (-1.50)	-0.513*** (-40.24)	-0.288* (-1.97)
Sobel's Test	5.961***	26.900***	36.583***	0.068	-2.590**
Observations	131016	131016	131016	131016	131016
Adj. R-squared	0.044	0.636	0.546	0.804	0.114

Table 29: 50k Institutional trading behavior (2008 financial crisis)

Table 29 shows results of extended model with 50k institutional trading indicator during the 2008 financial crisis. Sobel's test results are presented for different liquidity measures: quoted spread, effective spread, price impact, Amihud illiquidity ratio, and Kyle liquidity index. The t-statistics are reported in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	(1)	(2)	(3)	(4)	(5)
	Quoted Spread	Effective Spread	Price Impact	Amihud	Kyle Index
Crisis	0.000191*** (8.99)	0.0000841*** (7.41)	0.0000923*** (9.95)	-0.0266** (-3.19)	0.198* (2.24)
Institutional Trading (50k)	0.000529 (1.71)	-0.0000151 (-0.06)	-0.000248 (-1.49)	-0.517*** (-5.21)	-1.735 (-1.47)
CDS	0.000365*** (9.68)	0.000212*** (5.61)	0.000185*** (7.20)	0.114*** (10.88)	1.052*** (8.95)
Volatility	0.000286*** (9.01)	0.000132*** (5.66)	0.000122*** (7.96)	0.628*** (58.13)	3.801*** (24.70)
Volume	-0.000301*** (-6.76)	-0.0000138 (-0.39)	-0.0000330 (-1.34)	-0.518*** (-39.79)	-0.316* (-2.18)
Sobel's Test	3.042**	16.303***	22.651***	-2.973**	-2.905**
Observations	130946	130946	130946	130946	130946
Adj. R-squared	0.043	0.636	0.546	0.804	0.114

Table 30: Vector Autoregression for CDS Returns and Stock Returns(2010 Flash Crash)

Table 30 presents results from our VAR model during the 2010 flash crash. R_{CDS} and R_S are two return variables defined in our VAR model, representing CDS return and Stock return. Based on the selection criteria BIC, AIC, and HQIC, the optimal lag term is selected as 9. The t-statistics are reported in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

		R_{CDS}	R_S
R_{CDS}	t-1	0.019* (0.010)	-0.046 (0.032)
	t-2	0.007 (0.018)	-0.023 (0.015)
	t-3	-0.022 (0.014)	-0.016 (0.012)
	t-4	0.005 (0.008)	-0.012 (0.010)
	t-5	-0.014 (0.007)	-0.015 (0.010)
	t-6	0.012 (0.011)	0.009 (0.006)
	t-7	0.011 (0.011)	-0.004 (0.005)
	t-8	0.007 (0.011)	-0.003 (0.005)
	t-9	-0.003 (0.005)	0.002 (0.003)
R_S	t-1	-0.076802 (0.043649)	-0.018242 (0.011543)
	t-2	-0.033275 (0.018376)	-0.026092* (0.010966)
	t-3	-0.013100 (0.008426)	-0.004290 (0.004897)
	t-4	-0.015585 (0.009906)	-0.009128* (0.004059)
	t-5	-0.017642 (0.009513)	-0.017113*** (0.003159)
	t-6	-0.007693 (0.004693)	0.019687*** (0.003748)
	t-7	-0.001119 (0.002884)	0.003466 (0.008032)
	t-8	-0.005935 (0.006419)	0.006263 (0.005223)
	t-9	-0.005486 (0.004006)	0.000349 (0.003224)

Table 31: CDS Results during 2010 Flash Crash

Table 31 shows results of our extended model with interaction term (CDS \times Crisis) on different liquidity measures: quoted spread, effective spread, price impact, Amihud illiquidity ratio, and Kyle liquidity index during the 2010 flash crash. Regressions include stock fixed effects. Standard errors are clustered by firm. The t-statistics are reported in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	(1)	(2)	(3)	(4)	(5)	(6)
	Quoted Spread	Quoted Spread	Effective Spread	Effective Spread	Price Impact	Price Impact
Crisis	0.0000181*** (0.00000527)	0.000184** (0.0000595)	0.0000240* (0.0000100)	0.000167** (0.0000633)	0.0000237*** (0.00000668)	0.000186*** (0.0000444)
CDS	0.0000429** (0.0000137)	0.0000266 (0.0000148)	0.0000136 (0.0000210)	-0.000000443 (0.0000227)	0.0000168 (0.0000163)	0.000000788 (0.0000172)
Crisis \times CDS		0.0000361** (0.0000122)		0.0000311* (0.0000128)		0.0000354*** (0.00000899)
Volatility	0.0000533*** (0.00000358)	0.0000527*** (0.00000353)	0.0000892*** (0.0000147)	0.0000887*** (0.0000146)	0.0000829*** (0.00000939)	0.0000824*** (0.00000937)
Volume	-0.0000507*** (0.00000761)	-0.0000481*** (0.00000693)	-0.0000101 (0.0000159)	-0.00000783 (0.0000156)	-0.0000318** (0.00000993)	-0.0000292** (0.00000969)
Observations	52703	52703	52703	52703	52703	52703
Adj. R-squared	0.937	0.938	0.126	0.126	0.197	0.198

Table 32: CDS Result Continued (2010 Flash Crash)

Table 32 shows remaining results of our extended model with interaction term (CDS \times Crisis) on different liquidity measures: quoted spread, effective spread, price impact, Amihud illiquidity ratio, and Kyle liquidity index during the 2010 flash crash. Regressions include stock fixed effects. Standard errors are clustered by firm. The t-statistics are reported in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	(7)	(8)	(9)	(10)
	Amihud	Amihud	Kyle Index	Kyle Index
Crisis	0.174*** (0.0102)	0.289*** (0.0624)	0.302*** (0.0326)	0.873*** (0.202)
CDS	0.00783 (0.0385)	-0.00348 (0.0379)	0.179* (0.0793)	0.123 (0.0846)
CDS \times Crisis		0.0250 (0.0132)		0.124** (0.0409)
Volatility	0.484*** (0.0161)	0.484*** (0.0162)	0.593*** (0.0378)	0.591*** (0.0379)
Volume	-0.449*** (0.0152)	-0.447*** (0.0153)	0.0810 (0.0429)	0.0900* (0.0434)
Observations	52703	52703	52703	52703
Adj. R-squared	0.813	0.813	0.123	0.123

Table 33: 20k Institutional trading behavior (2010 flash crash)

Table 33 shows results of extended model with 20k institutional trading indicator during the 2010 flash crash. Sobel's test results are presented for different liquidity measures: quoted spread, effective spread, price impact, Amihud illiquidity ratio, and Kyle liquidity index. The t-statistics are reported in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	(1)	(2)	(3)	(4)	(5)
	Quoted Spread	Effective Spread	Price Impact	Amihud	Kyle Index
Crisis	0.0000178** (3.19)	0.0000243* (2.18)	0.0000222** (2.98)	0.166*** (16.70)	0.287*** (8.77)
Institutional Trading (20k)	-0.0000213 (-0.39)	0.0000286 (0.23)	-0.000126 (-1.53)	-0.621*** (-3.97)	-1.201** (-3.29)
CDS	0.0000427** (3.10)	0.0000138 (0.67)	0.0000159 (0.99)	0.00356 (0.09)	0.171* (2.18)
Volatility	0.0000529*** (12.61)	0.0000898*** (6.23)	0.0000803*** (8.45)	0.471*** (31.27)	0.569*** (15.05)
Volume	-0.0000498*** (-5.34)	-0.0000113 (-0.84)	-0.0000264** (-3.06)	-0.423*** (-27.64)	0.132** (2.98)
Sobel's Test	11.197***	5.226 ***	1.532	-3.958***	-0.160
Observations	52700	52700	52700	52700	52700
Adj. R-squared	0.937	0.126	0.197	0.813	0.123

Table 34: 50k Institutional trading behavior (2010 flash crash)

Table 34 shows results of extended model with 50k institutional trading indicator during the 2010 flash crash. Sobel's test results are presented for different liquidity measures: quoted spread, effective spread, price impact, Amihud illiquidity ratio, and Kyle liquidity index. The t-statistics are reported in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	(1) Quoted Spread	(2) Effective Spread	(3) Price Impact	(4) Amihud	(5) Kyle Index
Crisis	0.0000184*** (3.38)	0.0000249* (2.22)	0.0000222** (2.97)	0.166*** (16.51)	0.289*** (8.74)
Institutional Trading (50k)	0.0000396 (0.78)	0.000109 (0.60)	-0.000172 (-1.48)	-0.842*** (-5.95)	-1.561*** (-3.46)
CDS	0.0000430** (3.12)	0.0000140 (0.68)	0.0000161 (1.00)	0.00449 (0.12)	0.173* (2.21)
Volatility	0.0000540*** (13.15)	0.0000911*** (6.35)	0.0000800*** (8.48)	0.470*** (30.53)	0.568*** (14.97)
Volume	-0.0000520*** (-5.75)	-0.0000137 (-1.10)	-0.0000259** (-3.22)	-0.421*** (-27.65)	0.132** (2.90)
Sobel's Test	25.794***	11.3043***	8.079***	-2.830**	1.465
Observations	52697	52697	52697	52697	52697
Adj. R-squared	0.937	0.126	0.197	0.814	0.123

Table 35: Forecast Error Variance Decomposition

Table 35 reports the forecast error variance decomposition for our VAR model during the 2010 flash crash. R_{CDS} and R_S are two return variables defined in our VAR model, representing CDS return and Stock return. Sample periods are separated into two parts: the pre-”black swan” period and the ”black swan” period.

		Whole Sample Period												
Impulse Variable	Response Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
R_{CDS}	R_{CDS}	100%	99.8%	99.7%	99.7%	99.7%	99.7%	99.7%	99.7%	99.7%	99.7%	99.7%	99.7%	99.7%
	R_S	0.2%	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%
R_S	R_{CDS}	0.7%	0.7%	0.7%	0.7%	0.7%	0.7%	0.7%	0.7%	0.7%	0.7%	0.7%	0.7%	0.7%
	R_S	99.3%	99.3%	99.3%	99.3%	99.3%	99.3%	99.3%	99.3%	99.3%	99.3%	99.3%	99.3%	99.3%
		Pre-”Black Swan” Period												
		1	2	3	4	5	6	7	8	9	10	11	12	13
R_{CDS}	R_{CDS}	100%	99.8%	99.8%	99.8%	99.7%	99.7%	99.7%	99.7%	99.7%	99.7%	99.7%	99.7%	99.7%
	R_S	0	0.2%	0.2%	0.2%	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%
R_S	R_{CDS}	0.5%	0.5%	0.5%	0.5%	0.5%	0.5%	0.5%	0.5%	0.5%	0.5%	0.5%	0.5%	0.5%
	R_S	99.5%	99.5%	99.5%	99.5%	99.5%	99.5%	99.5%	99.5%	99.5%	99.5%	99.5%	99.5%	99.5%
		”Black Swan” Period												
		1	2	3	4	5	6	7	8	9	10	11	12	13
R_{CDS}	R_{CDS}	100%	99.5%	99.4%	99.4%	99.3%	99.3%	99.2%	99.2%	99.2%	99.2%	99.2%	99.2%	99.1%
	R_S	0	0.5%	0.6%	0.6%	0.7%	0.7%	0.8%	0.8%	0.8%	0.8%	0.8%	0.8%	0.9%
R_S	R_{CDS}	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%
	R_S	99%	99%	99%	99%	99%	99%	99%	99%	99%	99%	99%	99%	99%

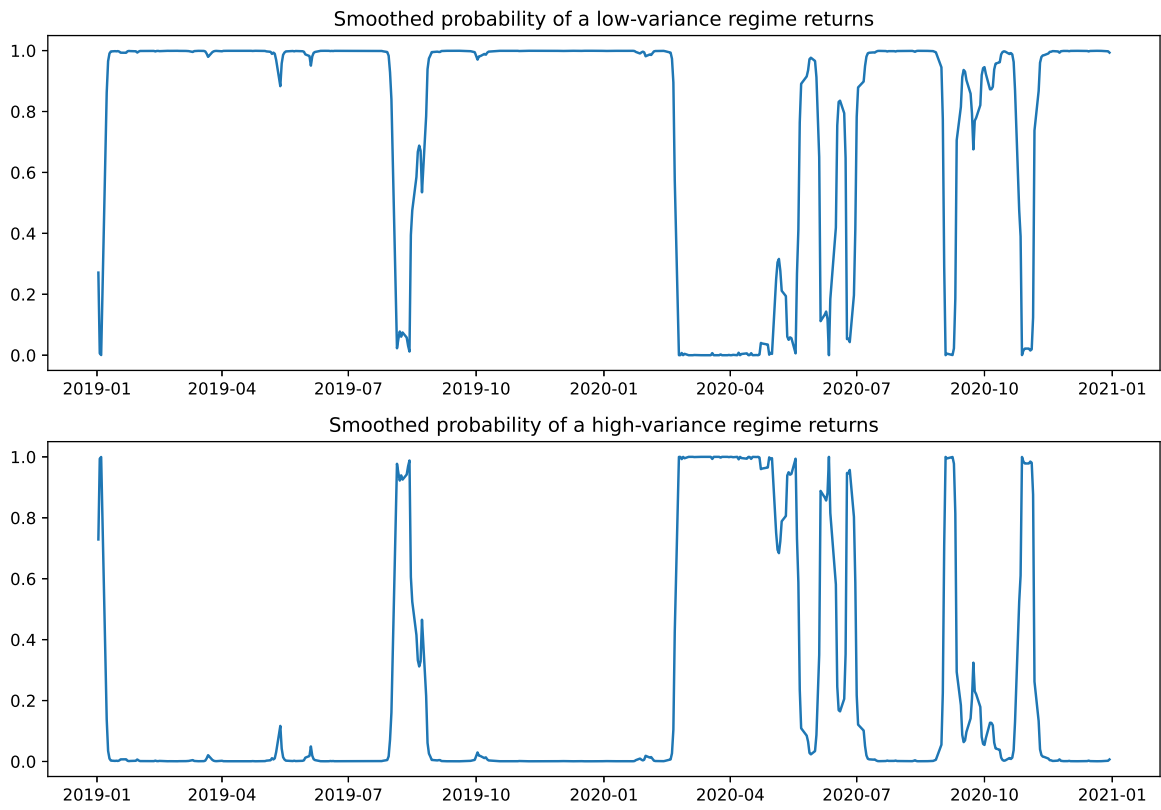


Figure 1: Results of Markov regime switching model.

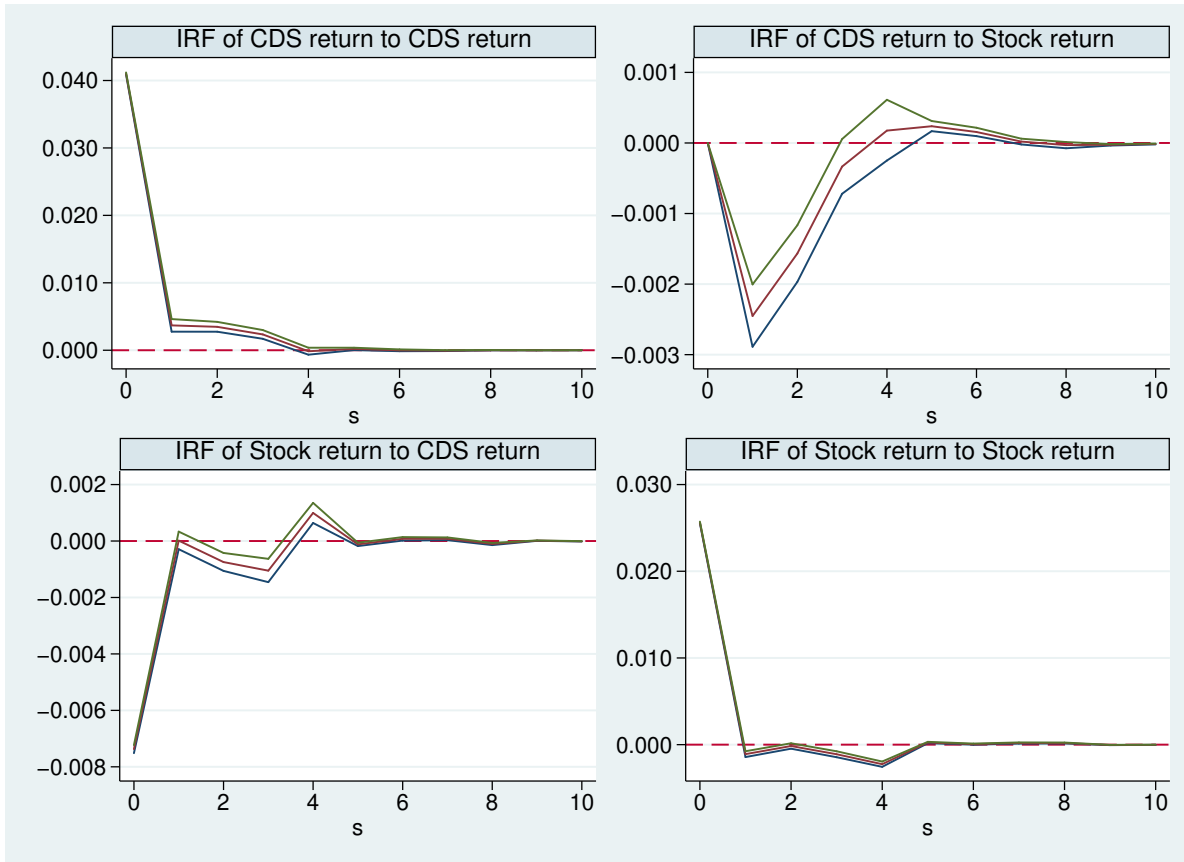


Figure 2: IRF results across the whole sample period. CDS return and Stock return represent two variables defined in our VAR model: R_{CDS} and R_S . The first row presents responses of CDS return to two variables, whereas the second row shows responses of Stock return.

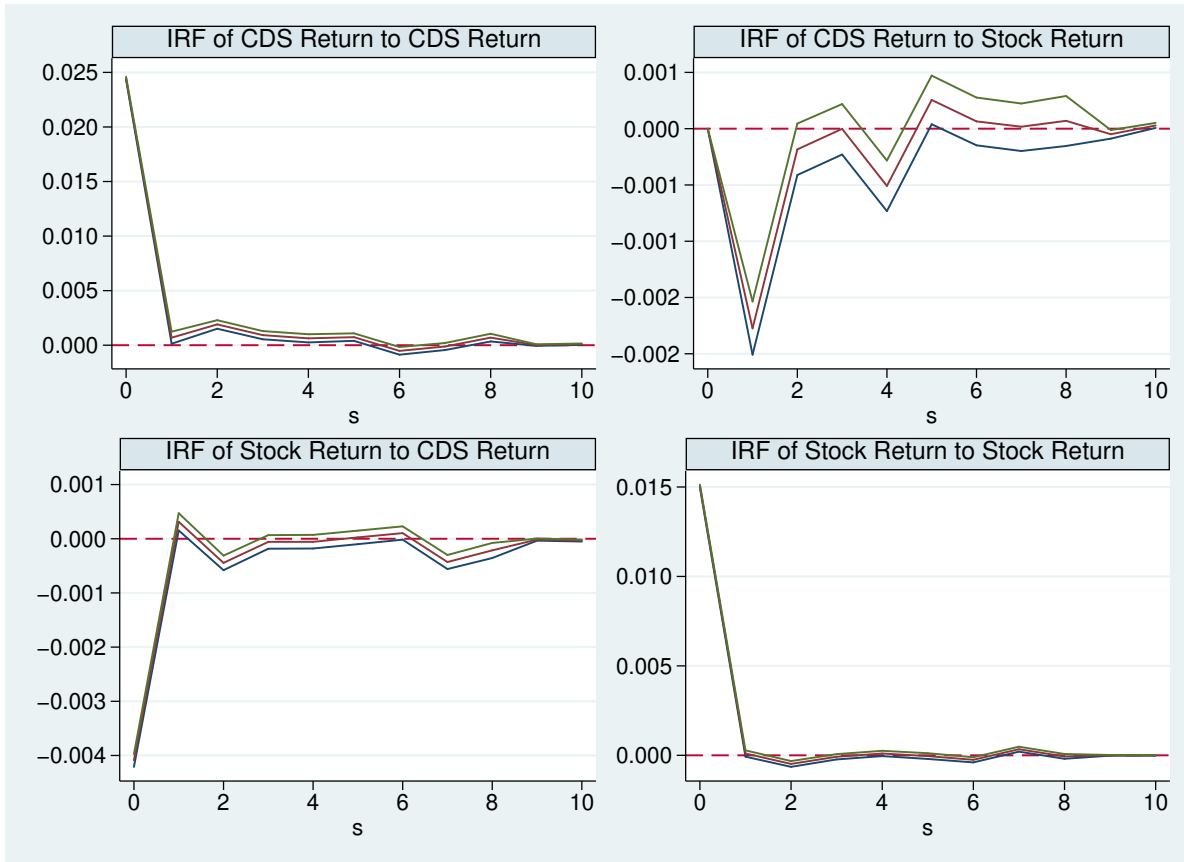


Figure 3: IRF results across pre-”black swan” period). CDS return and Stock return represent two variables defined in our VAR model: R_{CDS} and R_S . The first row presents responses of CDS return to two variables, whereas the second row shows responses of Stock return.

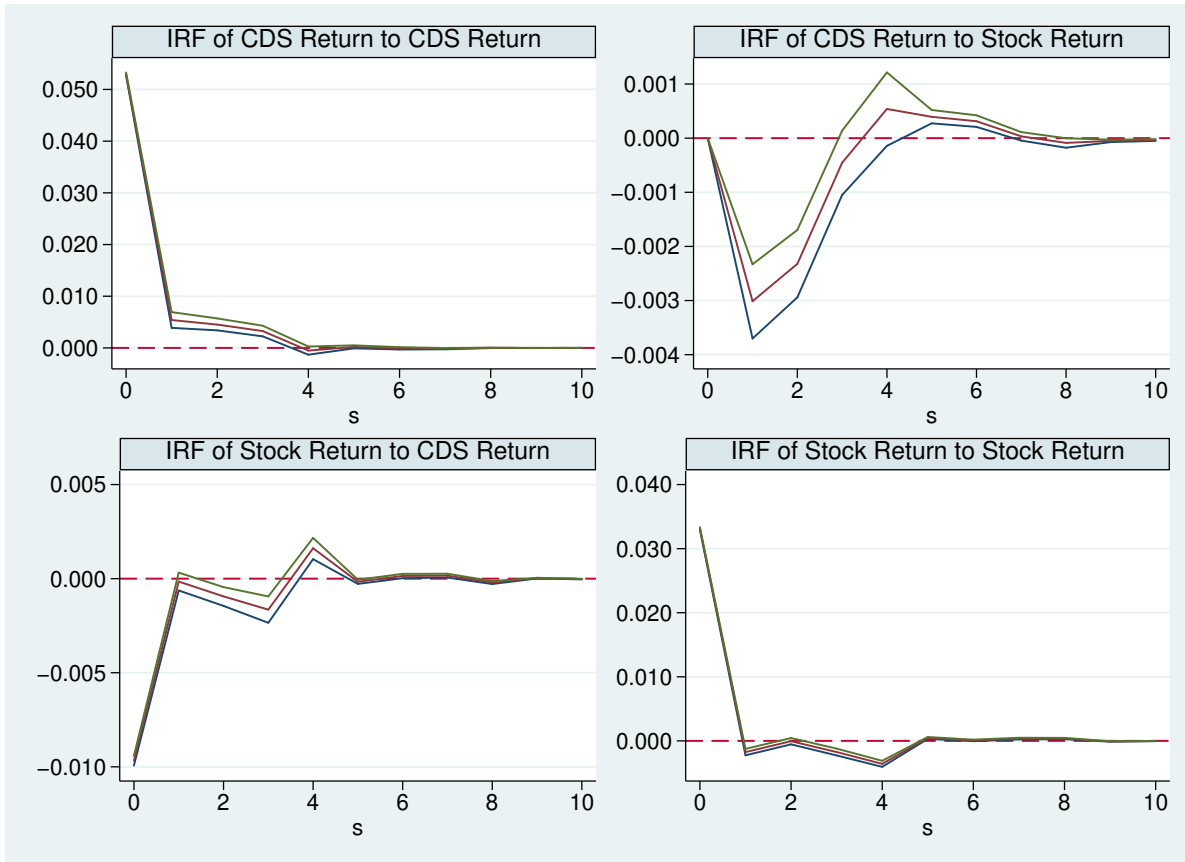


Figure 4: IRF results across "black swan" period. CDS return and Stock return represent two variables defined in our VAR model: R_{CDS} and R_S . The first row presents responses of CDS return to two variables, whereas the second row shows responses of Stock return.

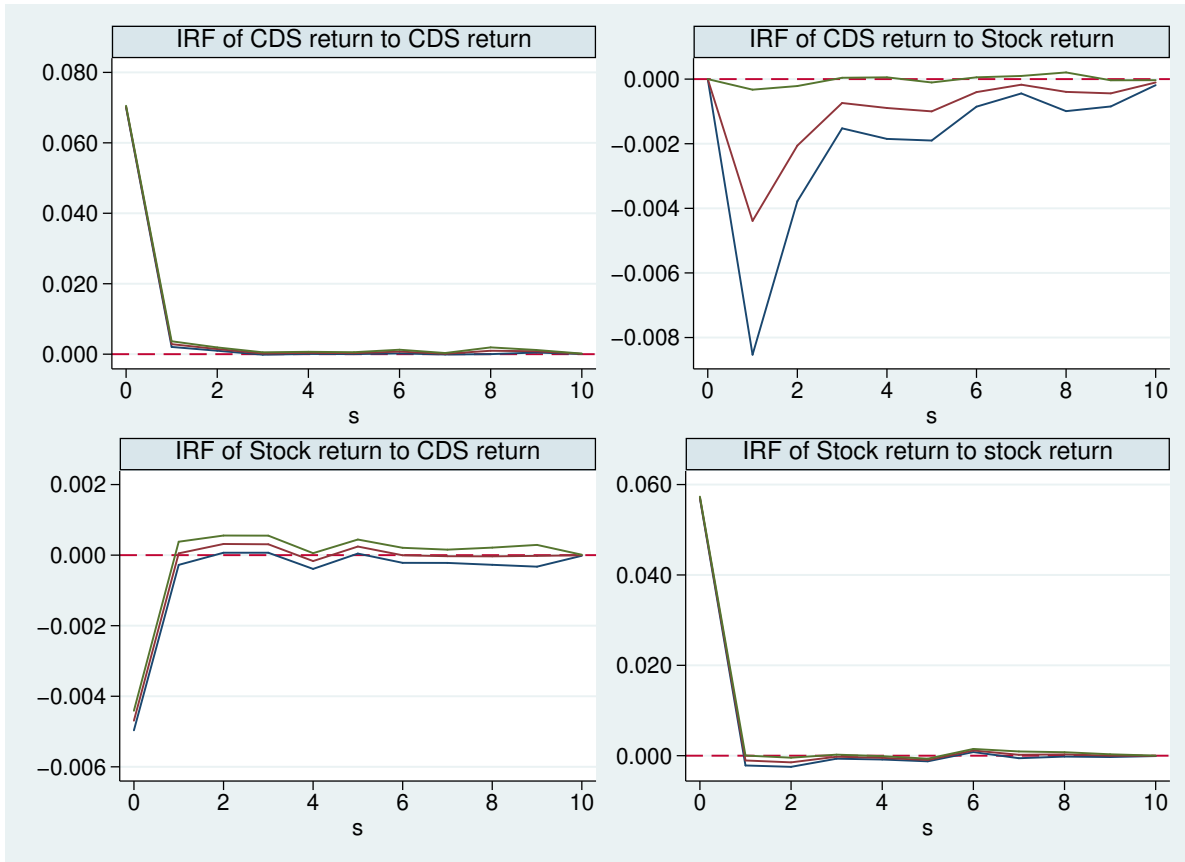


Figure 5: IRF results during 2008 financial crisis. CDS return and Stock return represent two variables defined in our VAR model: R_{CDS} and R_S . The first row presents responses of CDS return to two variables, whereas the second row shows responses of Stock return.



Figure 6: IRF results during 2010 flash crash. CDS return and Stock return represent two variables defined in our VAR model: R_{CDS} and R_S . The first row presents responses of CDS return to two variables, whereas the second row shows responses of Stock return.

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