Essays on Sovereign Credit Default Swaps

DISSERTATION
of the University of St.Gallen,
School of Management,
Economics, Law, Social Sciences
and International Affairs
to obtain the title of
Doctor of Philosophy in Finance

submitted by

Yi Li

from

China

Approved on the application of

Prof. Dr. Angelo Ranaldo

and

Prof. Paul Söderlind, PhD

Dissertation no. 5001

Difo-Druck GmbH, Untersiemau 2020

The University of St.Gallen, School of Management, Economics, Law, Social Sciences and International Affairs hereby consents to the printing of the present dissertation, without hereby expressing any opinion on the views herein expressed.

St.Gallen, May 25, 2020

The President:

Prof. Dr. Bernhard Ehrenzeller

For My Mother and Father.
Danke.

Acknowledgements

I would like to thank my supervisor, Prof. Angelo Ranaldo, for his continued patience and support throughout my Ph.D study. Furthermore, I want to thank my co-supervisor, Prof. Paul Söderlind, for his insight and support. Thanks also go to the conference and seminar participants for their valuable feedback.

Finally, I would like to dedicate this thesis to my parents, in particular in memory of my beloved mother, Wu Shengmei.

Shanghai, June 2020 Yi Li

Contents

Summary

This dissertation consists of three essays on sovereign credit default swaps (CDSs).

The first essay studies the relationship between the China sovereign and bank CDS spreads and the determinants of the China sovereign CDS spread changes using the copula model and regression analysis. Our results show a strengthened tail dependence of sovereign-bank CDS pairs, and the tail dependence coefficient is higher for commercial banks than for policy banks. U.S. stock market returns, high-yield spread changes, and changes in foreign currency reserve/GDP ratio are important global and macroeconomic factors in explaining variation in China's sovereign credit risk. Domestic factors play important roles in explaining the China sovereign CDS spread changes, especially during the trade war period.

The second essay studies the explanatory power of country-level and market-level volatilities for Western European sovereign CDS spreads during the European sovereign debt crisis and short-selling ban periods. We include both historical and option-implied volatility measures. Our results show that the changes in country-specific and market-level volatilities are important factors in explaining the sovereign CDS spread changes and that option-implied volatility contains more information than historical volatility. Our results also raise the question of whether there should be a universal ban on short selling.

The last essay examines the dependence structure of the sovereign CDS spreads between the U.S. and 36 countries located in Western Europe, Central & Eastern Europe, Latin America, and Asia. Our results show that the tail dependence coefficients of U.S.-Western European and U.S.-Central & Eastern European sovereign CDS pairs are non-zero. We perform a cross-sectional analysis to study the determinants of co-dependence. The results show that higher trade flow and larger foreign exposure of the U.S. banking system are associated with a higher probability of large joint increases in the sovereign credit risks of the U.S. and European countries.

Zusammenfassung

Diese Dissertation besteht aus drei Aufsätzen über Kreditausfall-Swaps (CDSs) für Staatsanleihen. Der erste Aufsatz untersucht die Beziehung zwischen den CDS-Spreads des chinesischen Staates und der Banken, sowie die Einflussfaktoren für die Veränderungen der CDS-Spreads des chinesischen Staates anhand des Copula-Modells und der Regressionsanalyse. Unsere Ergebnisse zeigen eine verstärkte Tail-Abhängigkeit bei den CDS-Paaren für Staaten und Banken, und der Tail-Abhängigkeits-Koeffizient ist höher für Geschäftsbanken als für politische Banken. Die USAktienmarktrenditen, die Änderungen der Hochzins-Spreads und die Änderungen der Devisenreserve im Verhältnis zum BIP sind wichtige globale und makroökonomische Faktoren, die Schwankungen des staatlichen Kreditrisikos Chinas erklären. Bei der Erklärung von Änderungen in den CDS-Spreads des chinesischen Staates, insbesondere während des Handelskrieges, spielen inländische Faktoren eine wichtige Rolle.

Der zweite Aufsatz untersucht die Erklärungskraft von Volatilitäten auf Länder- und Marktebene in Bezug auf die CDS-Spreads westeuropäischer Staatsanleihen während der europäischen Staatsschuldenkrise und während des Leerverkaufsverbots. Wir beziehen sowohl historische als auch implizite Volatilitätsmaße ein. Unsere Ergebnisse zeigen, dass die Veränderungen der länderspezifischen und marktbezogenen Volatilitäten wichtige Faktoren zur Erklärung der Veränderungen der CDS-Spreads für Staatsanleihen sind und dass die implizite Volatilität mehr Informationen enthält als die historische Volatilität. Unsere Ergebnisse führen auch zu der Frage, ob die Einführung eines allgemeinen Verbots von Leerverkäufen erforderlich ist. Der letzte Aufsatz untersucht die Abhängigkeitsstruktur der staatlichen CDS-Spreads zwischen den USA und 36 Ländern in Westeuropa, Mittel- und Osteuropa, Lateinamerika und Asien. Unsere Ergebnisse zeigen, dass die Tail-Abhängigkeits-Koeffizienten der CDS-Paare von US-Westeuropa und US-Mittel- und Osteuropa nicht Null sind. Um die Determinanten der Co-Abhängigkeit zu untersuchen, führen wir eine Querschnittsanalyse durch. Die Ergebnisse zeigen, dass die höheren Handelsströme und das größere Auslandsrisiko des US-Bankensystems mit höherer Wahrscheinlichkeit eines starken gemeinsamen Anstiegs des Staatskreditrisikos der USA und der europäischen Länder verbunden sind.

1. Understanding China Sovereign Credit Default Swap

Author: Yi Li*

Abstract:

This paper provides an in-depth study of the China sovereign credit default swap (CDS). We use two approaches, the copula model and regression analysis, to study the relationship between the China sovereign and bank CDS spreads and the determinants of the China sovereign CDS spread changes. The results of the copula model show a strengthened tail dependence of sovereign−bank CDS pairs, which suggests a higher likelihood of joint extreme movements. The tail dependence coefficient of sovereign−bank CDS pairs is higher for commercial banks than for policy banks. This implies a higher probability of simultaneous large increases in China's sovereign and commercial bank credit risks. U.S. stock market returns and high-yield spread changes are two important global factors in explaining variation in China's sovereign credit risk, while the foreign currency reserve/GDP ratio is the only important macroeconomic variable. Domestic factors, such as the orthogonalized local stock market returns, orthogonalized change in the CBOE China ETF volatility index (VXFXI), and the change in offshore exchange rates play important roles in explaining the China sovereign CDS spread changes, especially during the U.S.-China trade war period.

Keywords: Sovereign CDS; Bank CDS; Copula; Tail Dependence Coefficient; Determinants

JEL Classification: C52, G01, G10, G15

*I am grateful for valuable comments and suggestions received from Angelo Ranaldo, Paul Söderlind, and the seminar participants at the St. Gallen university and the 2019 China Conference of CEA (UK/Europe) in Shanghai.

1.1 Introduction

China has become the world's second largest economy as of 2010. However, its economic growth has been slowing down in recent years. Meanwhile, the net notional amount of China sovereign credit default swaps (CDSs) jumped from $7.420 billion to $13.042 billion in 2014, which makes the China sovereign CDS one of the largest net insured single-name sovereign CDS contracts. PIMCO, a sizable liquidity provider on this contract, suggests that this increasing net notional amount of China sovereign CDS is potentially caused by the rising concerns of its domestic banking system, in areas such as shadow banking, and the economic slow down.[1] These arguments motivate us to study the relationship between China's sovereign and bank credit risks as well as the other important determinants of China sovereign CDS spreads.

This paper intends to achieve two goals. First, we set out to study the dynamic relationship between China sovereign CDS spreads and bank CDS spreads. In particular, we want to explore the probability of simultaneous large increases in sovereign credit risk and bank credit risk. To achieve this purpose, we use the copula model to access the risk of joint extreme movements in default probability via tail dependence coefficient. Meine et al. (2016) suggest a copula model has the advantage to capture the complete dependence structure in a joint return distribution that linear correlations cannot fully describe. We consider both static and dynamic copula in our analysis. The advantage of dynamic copula is that it produces time-varying tail dependence coefficients; therefore, we do not need to manually separate the full sample period into multiple sub-periods. By using the copula model and the model-implied tail dependence coefficient, we address the following questions: Are China sovereign CDS spreads more likely to get extreme joint upward movement with commercial bank CDS spreads or policy bank CDS spreads? And has the relationship between China sovereign and bank CDS strengthened over the years?

Our second object is to study the determinants of China sovereign CDS spread

[1]According to Reuters' article: "China CDS trading booms", PIMCO became more active in China sovereign CDS contracts amid rising fears over the country's shadow banking system and an economic slowdown. In fact, PIMCO sold around one-fifth of the net notional amount of China sovereign CDS contracts by the end of Q1 2014.

changes. We investigate this issue by performing regression analysis, which is the commonly used method in the literature to study sovereign CDS spread changes (Longstaff et al., 2011; Eyssell et al., 2013; Dieckmann and Plank, 2012; Fontana and Scheicher, 2016). We perform regression analyses in both daily and monthly frequencies. The daily time series regression is used to test whether local and global factors have explanatory powers for China sovereign CDS spread changes. We include the commonly used local and global factors as well as implied volatility as an additional local factor in our daily regression analysis. The macroeconomics factors are not considered in the daily time series regression as they are typically updated infrequently. In order to obtain those variables in a daily frequency, we need to use linear or spline interpolation, which might create bias and lead to a questionable regression result. For instance, Eyssell et al. (2013) use Debt-over-GDP as one of the local factors to study the daily China sovereign CDS spread changes and found the estimated coefficient is negatively significant at the 1% level. Therefore, we only consider these macroeconomic variables in the monthly regression analysis. To study the explanatory power of local and global variables for China sovereign CDS spreads in different periods (e.g., normal period and crisis period), we apply the Bai and Perron (2003) structural break test, which separates the full sample period into four sub-periods, on China sovereign CDS returns. We perform the daily regression analysis for each of those four sub-periods to address the following two questions: first, what are the important local and global factors in explaining the daily China sovereign CDS spread changes? Second, do local factors become more important for China sovereign CDS spreads during the crisis period, such as the U.S.−China trade war period? We use monthly time series regression to study the explanatory powers of macroeconomic and investment-flow variables. The question we want to address is: What are the important macroeconomic or investment-flow variables in explaining the monthly China sovereign CDS spread changes?

We need to stress that domestic bank CDS returns are only used in the copula model and are not considered as one of the local factors in our regression analysis. First, domestic bank CDS returns are typically not used in the literature as one of the determinants for sovereign CDS spread changes when performing the regression analysis. Second, we might need to address the possible endogeneity issue when including this variable in regression analysis. Kallestrup et al. (2016) suggest there is a possibility of endogeneity of bank CDS premia, since sovereign CDS and bank CDS spreads might be determined jointly. In order to address this issue, we would need to perform a 2SLS regression analysis using an instrument for bank CDS returns. However, finding a good instrument is a difficult task. For instance, Kallestrup et al. (2016) test the possibility of using a bank's leverage as the instrument for bank CDS returns and find it to be a weak instrument. Based on the above reasons, we do not include bank CDS returns as one of the local factors in our regression analysis. Nevertheless, we still provide the estimation results of the daily time series regression, which includes bank CDS returns as one of the local factors in the Appendix.

Our results on the joint extreme movements of China sovereign and bank CDS spreads bring new light to academics, investors, and policymakers. For academics, we set the foundation of the study on China sovereign and bank CDS spreads co-movements by providing the first study on the tail dependence analysis. For investors, our results of the higher likelihood of simultaneous large increases in sovereign and bank credit risks suggest investors should closely watch the condition of China domestic banking system when monitoring China sovereign credit risk. For policymakers, our results demonstrating the strengthened sovereign-bank relationship suggest they should pay more attention to the health of domestic banks to avoid the future risk spillover through potential government bailout.

Our results on the determinants of China sovereign CDS spread changes deliver new insight to academics, investors, and policymakers as well. On the academic side, we show the change in offshore exchange rate and the CBOE China ETF Volatility Index (VXFXI) are two important local factors besides the domestic stock market returns in explaining the China sovereign CDS spread changes. Both factors are not considered in Eyssell et al. (2013) but should be included as domestic factors in future study. For investors, our results suggest domestic factors play an equally important role as global factors in assessing the China sovereign credit risk during crisis periods. This implies investors should also pay attention to the local economic indicators when pricing the China sovereign credit risk. For policymakers, our results show exchange rate, stock market volatility and returns play an important role for sovereign credit risk, especially during crisis periods. This calls for a closer monitoring and risk assessment in stock exchange and currency exchange markets when a local economy is under pressure.

We formulate two main hypotheses for testing the relationship between China sovereign and bank CDS spreads and the determinants of China sovereign CDS spread changes. Our first hypothesis relates to the relationship between China sovereign and bank credit risks. Acharya et al. (2014) model a loop between sovereign and bank credit risks. The cost of the government bailout of a distressed financial sector increases the sovereign credit risk, which in turn weakens the financial sector by the decreased value of its holdings of government bonds and guarantees. Acharya et al. (2014) also find the increasing credit risk of banks, measured by bank CDS spreads, has almost no relation with the sovereign credit risk, measured by sovereign CDS spreads, during the pre-bailout period. During the bailout period, a decreasing bank CDS spread is associated with an increasing sovereign CDS spread. After the bailout, bank CDS spreads and sovereign CDS spreads strongly co-move. Cooper and Nikolov's (2018) model shows that the equity cushions can break the "diabolic loop" between banks and sovereigns from the banks' side. They show that banks have no incentive to issue equity in the equilibrium with government bailout. Banks that hold adequate capital against sovereign risks can absorb the loss from government default and become insulated from the development in debt markets. However, when the government bailout is expected to be provided ex-post, banks find themselves to have no incentive to self-insure by building up a capital buffer. In the framework of Cooper and Nikolov (2018), banks' weak incentives to issue equity is a key reason why the "diabolic loop" exists in the first place. Farhi and Tirole's (2018) model also states the basic mechanism of the "doom loop." A weakening financial balance sheet leads to a weakening sovereign balance sheet because it prompts bailout, which increases the stock of public debt. Meanwhile, a weakening sovereign balance sheet directly affects the financial balance sheet because banks hold public debt.

The Chinese government started to bail out domestic banks in 1998 due to the non-performing loans (NPLs) problem. The daily China sovereign CDS spreads and the CDS spreads of four Chinese Banks show a high degree of co-movement (Figure 1.1). The commonality in sovereign CDS spread and commercial banks' CDS spreads are as expected and consistent with the empirical findings in Acharya et al. (2014) that bank CDS spreads and sovereign CDS spreads strongly co-move after the government bailout. Moreover, China launched a deposit insurance system on May 01, 2015, which lays the foundation for freeing up rates by ensuring protection for savers. The system establishes that, even if competition for deposits leads to excessive risk-taking and bank failure, deposits up to around $80,600 would be insured. This rollout of deposit insurance in 2015 highlights the possibility of bank failure, which reveals the hidden pressure embedded in the China banking system. However, whether bank failure is allowed in China is still questionable. In fact, a regional commercial bank, Baoshang bank, was bailed out in May 2019. It was the first such action in about 20 years. Two more banks, JunZhou Bank and HengFeng Bank, were bailed out as well in 2019. The evidence of increasing pressure in the Chinese banking system and the increasing number of government bailouts motivate us more to study the dynamic relationship between China sovereign and bank credit risks. This dynamic relationship is measured using the copula model implied tail dependence coefficient. The tail dependence coefficient measures the asymptotic likelihood that two variables go up at the same time (Chollete et al., 2011). A higher tail dependence coefficient of sovereign−bank CDS pairs indicates a higher probability of simultaneous large increases in sovereign and bank credit risks. Based on the above evidence of increasing pressure in the domestic banking sector as well as more recent cases of government bailouts, we build our first hypothesis as: the tail dependence coefficient of China sovereign−bank CDS pairs is non-zero and has increased in recent years.

Our second hypothesis relates to the role of local and global variables in explaining the China sovereign CDS spread changes during normal and crisis periods. Longstaff et al. (2011) study the determinants of 26 developed and emerging-market countries' sovereign CDS spread changes. They find the sovereign credit risk is driven more by global market factors, such as U.S. stock and high-yield market factors, than by country-specific fundamentals. Augustin (2018) runs the same monthly regression as in Longstaff et al. (2011) by extending the dataset from 26 countries to 44 countries. They find most of the global variables are statistically insignificant in explaining the sovereign CDS spread changes for distressed countries, while the domestic variables are typically statistically significant. Inspired by the empirical findings in Augustin (2018), we build our second hypothesis as: global factors play an important role in explaining the China sovereign CDS spread changes during the normal period, while local factors become more important in explaining the China sovereign CDS spread changes during a crisis period, such as the U.S.−China trade war period.

We include the five-year China sovereign CDS spreads and the five-year CDS spreads of four Chinese banks to study the extreme co-movements of the sovereign and bank CDS spreads. The four banks include two commercial banks and two policy banks. The two commercial banks are Bank of China (BoC) and Industrial and Commercial Bank of China (ICBC). Both banks can represent the China banking system in terms of their systemic importance and size. To be specific, BoC has been the world's fourth largest bank by total assets since 2015 according to Standard & Poor's (S&P) global market intelligence report. It has also been classified as a systemically important financial institution by the Financial Stability Board (FSB) since 2011. Meanwhile, ICBC is the world's largest bank by total assets and has been classified as a systemically important financial institution since 2013. The two policy banks are China Development Bank (CDB) and Export-Import Bank of China (Chexim). Both banks are the stakeholders of the Silk Road Fund and are heavily involved in the "Belt and Road Initiative" projects. Therefore, we believe both CDB and Chexim can be good representatives of China policy banks, especially from the view of foreign investors due to both banks' business ties with oversea projects. For China sovereign CDS, BoC CDS, CDB CDS and Chexim CDS, data are avaliable from January 01, 2013 to November 23, 2018. For ICBC CDS, data are avaliable from September 15, 2017 to November 23, 2018.

To study the determinants of daily China sovereign CDS spread changes, we include both local and global factors as explanatory variables. To study the determinants of monthly China sovereign CDS spread changes, we include additional macroeconomics and investment-flow variables. The local factors comprise the orthogonalized local stock market returns, orthogonalized bank stock returns, percentage changes in offshore exchange rates, percentage changes in ten-year China government bond yields, percentage changes in slope of yield curve, and the orthogonalized percentage changes in the VXFXI. We use the orthogonalized series to improve the identification following Dieckmann and Plank (2012). For instance, we use the orthogonalized local stock market returns to remove the impact of the overnight movements of the U.S. stock market on the China stock market. The orthogonalized local stock market returns are constructed as the sum of intercept and residuals from a regression of local stock market returns on the lagged U.S. stock market returns. Similarly, to remove the impact of the domestic stock market's performance and the movements of the overnight U.S. bank stock market on the China bank stock returns, we use the orthogonalized bank stock returns which are constructed as the sum of intercept and residuals from a regression of domestic bank stock returns on the lagged U.S. bank index returns and the orthogonalized local stock market returns. The VXFXI is highly correlated with VIX because it is calculated based on the iShares China Large-Cap ETF traded in the United States. To improve identification, we construct the orthogonalized percentage changes in VXFXI as the sum of intercept and residuals from a regression of percentage changes in VXFXI on the percentage changes in VIX.

We include U.S. stock market returns, percentage changes in U.S. investment grade yield spreads and high-yield spreads as global factors in our daily regression analysis. U.S. stock market returns are the excess returns calculated as the Morgan Stanley Capital International (MSCI) USA index returns minus the risk-free rate. Investment grade yield spreads are the yield spreads between S&P 500 BBB and S&P 500 AAA U.S. corporate bond indices. High-yield spreads are the yield spreads between S&P 500 BB and S&P 500 BBB U.S. corporate bond indices. Both U.S. stock market returns and the change in U.S. high-yield spreads are shown to be the most important global factors in Longstaff et al. (2011). To perform the monthly regression analysis, we include the additional macroeconomic and investment-flow variables, specifically: monthly changes in real interest rates; external debt over GDP ratio; foreign currency reserves over GDP ratio; Terms of Trade volatility; government budget balance over GDP ratio; economic policy uncertainty; and equity and bond net flows. For those quarterly updated variables, we use linear interpolation to transform them into monthly frequency. We acknowledge that all the above macroeconomic variables can be classified as local factors. In fact, Longstaff et al. (2011) and Augustin (2018) use foreign currency reserves as local variables in their monthly regression analysis, and Eyssell et al. (2013) use debt over GDP and real interest rates as local variables in their regression analysis. In our paper, we define those variables as the macroeconomic variables to avoid the confusion and use them only in the monthly regression analysis. Our reasoning is that Eyssell et al.(2013) include these macroeconomic variables in daily regression analysis and find their coefficients are statistically significant with the wrong signs.

Our full sample period is from January 01, 2013 to November 23, 2018. We separate this into four sub-periods, which are identified by using the Bai and Perron (2003) structural break test on China sovereign CDS returns. Those four sub-periods are defined as follows: 1) pre-stock market turbulence period from January 01, 2013 to September 05, 2014; 2) stock market turbulence period from September 08, 2014 to February 11, 2016;[2] 3) post-stock market turbulence period from February 12, 2016 to January 05, 2018; 4) U.S.–China trade war period from January 08, 2018 to November 23, 2018.[3] By performing the daily regression analysis for each of the four periods, we can investigate whether local factors become more important in explaining the sovereign CDS spread changes during a crisis period, such as the U.S.–China trade war period.

We use both dynamic and static copulas to study the co-movements of China's sovereign and bank CDS spreads. The copula model implied tail dependence coefficient can help us to measure the probability of simultaneous large increases in China's sovereign and bank credit risks. Using the copula model to study the dependence structure of two assets' prices can also be found in Reboredo (2011) and Chollete et al. (2011). We are the first, to our best knowledge, to study the co-movements of the China sovereign and bank CDS spreads using the copula model. To test what are the important local and global factors in explaining the China sovereign CDS spread changes, we perform the daily regression analysis for each of the four sub-periods. The monthly time series regression is used to test the explanatory power of macroeconomic and investment-flow variables after controlling for the local and global variables. Our choice of using time series regression to study the determinants of sovereign CDS spread changes follows Longstaff et al. (2011), Eyssell et al. (2013), Dieckmann and Plank (2012), and Fontana and Scheicher

[2]During this stock market turbulence period, Chinese stock market was on a roller coaster ride. To be specific, the stock market bubble started around mid-2014 and crashed in mid-June 2015 (Sornette et al., 2015). The onshore Shanghai composite index reached its peak at June 12, 2015, and lost 32% of its value between June 12, 2015 and July 8, 2015. During the same period, the MSCI China index lost around 20% of its value and reached its bottom around February 2016.

[3]The trade war between China and the United States began in January 2018 when U.S. announced tariffs on solar panels, which affected China the most. Corresponding, the China sovereign CDS spreads started to increase at January 2018.

(2016).

Our results of the copula model show that the tail dependence coefficients are non-zero for all bank-sovereign CDS pairs. Moreover, the tail dependence coefficient is higher for the commercial bank-sovereign CDS pair than for the policy bank-sovereign CDS pair. To be specific, the average tail dependence coefficient for the commercial bank-sovereign CDS pair is 0.393, while the average tail dependence coefficient for the policy bank-sovereign CDS pair is 0.057. The dynamic structure of the tail dependence coefficient indicates an increase in the tail dependence coefficient for the BoC and sovereign CDS pair, as well as the CDB and sovereign CDS pair. Figure 1.3 shows the tail dependence coefficient started to increase for the BoC-sovereign CDS pair and the CDB-sovereign CDS pair in mid-2016 and the beginning of 2017. Although we cannot observe a clear increase in the tail dependence coefficient for the Chexim-sovereign CDS pair, the dependence coefficient is stabilized at a slightly higher level after 2017. To be specific, the tail dependence coefficient is within the range [0.0424, 0.0788] from 2017 to 2018 and is within the range [0.0301, 0.0987] from 2013 to 2016. Therefore, our results confirm the first hypothesis that the tail dependence coefficient of the China sovereign-bank CDS pair is non-zero and has increased in recent years.

Our results of daily time series regression confirm the second hypothesis on the important role of local factors during the crisis period. To be specific, we find the coefficients on the orthogonalized change in implied volatility and the change in offshore exchange rate are statistically significant for the U.S.−China trade war period and the post−stock market turbulence period after controlling for the global factors. Moreover, the combined explanatory power of local variables are high in the U.S.−China trade war period. To be precise, our results show the R^2 of local variables is 0.231 in the trade war period. This is comparably the same as the R^2 of global variables, which is 0.252. Our results of daily time series regression also confirm the important role of global factors in explaining the China sovereign CDS spread changes. The most important global factors for China sovereign CDS spread changes are the U.S. stock market returns and the percentage changes in U.S. high-yield spreads. This is consistent with the empirical findings in Longstaff et al. (2011). Our results of monthly time series regression show that the foreign currency reserve/GDP ratio is the only important macroeconomic variable.

Our analysis contributes to two strands of the literature. First, we contribute to the literature on the relationship between sovereign and bank credit risks. The theoretical models largely build on the two-way feedback loop of sovereign and bank credit risks. In the Acharya et al. (2014) model, the cost of a government bailout of a distressed financial sector increases the sovereign credit risk, which in return weakens the financial sector by the decreased value of its holdings of government bonds and guarantees. The Cooper and Nikolov's (2018) model shows banks' weak incentives to issue equity is a key reason why the "diabolic loop" exists in the first place. The Farhi and Tirole's (2018) model states the basic mechanism of the "doom loop." A weakening financial balance sheet leads to a weakening sovereign balance sheet through the increasing stock of public debt from bailout, while a weakening sovereign balance sheet affects the financial balance sheet through the banks' holding of public debt. On the empirical side, Avino and Cotter (2014) uses a vector error correction model (VECM) to study the long-run relationship between sovereign CDS returns and domestic bank CDS returns. They show a clear leading role of bank CDS spreads for developed countries, such as Germany and Sweden. The leading role of sovereign CDS spreads is found for distressed economies, such as Portugal and Spain. We use the copula model in this paper to study the joint extreme movements of sovereign and bank CDS spreads, which reveals the probability of simultaneous large increases in sovereign and bank credit risks.

Second, we contribute to the literature on the determinants of sovereign CDS spread changes. Eyssell et al. (2013) perform regression analysis to study the determinants of China sovereign CDS spread changes from January 2001 to December 2010. Their results show the local stock market returns are an important factor in explaining the China sovereign CDS spread changes. However, the results of other factors are quite puzzling. For instance, they find the coefficient on the change in Debt-over-GDP ratio is negatively significant in both daily and monthly regression analyses. Moreover, the coefficient on the change in real interest rate is positively significant in daily regression analysis. Nevertheless, their results justify our choice of considering the macroeconomic variables only in monthly regression. Our paper studies the determinants of sovereign CDS spread changes from January 2013 to November 2018 by performing regression analyses in both daily and monthly frequencies. Our results show the coefficient on the percentage changes in offshore exchange rates is statistically significant for the trade war period and post-stock market turbulence period in daily regression analysis. This result adds to the literature because the exchange rate is not considered as one of the explanatory variables in Eyssell et al. (2013). Our results also show that the coefficient on the orthogonalized percentage changes in implied volatility is statistically significant for the trade war period and post-stock market turbulence period. This holds for both daily and monthly regression analyses. This result adds to the literature because implied volatility is not considered in Eyssell et al. (2013) as well. Longstaff et al. (2011), Augustin (2018), and Dieckmann and Plank (2012) also study the determinants of sovereign CDS spread changes. Longstaff et al. (2011) find the sovereign credit risk is driven more by global market factors, such as U.S. stock and high-yield market factors, than by country-specific fundamentals. Augustin (2018) find most of the global variables are statistically insignificant in explaining the sovereign CDS spread changes for distressed countries, while the domestic variables are typically statistically significant. Dieckmann and Plank (2012) show the state of the world financial system have strong explanatory power for the behavior of European sovereign CDS spreads.

The remainder of the paper is organised as follows: Section 2 describes the mechanics of the CDS market and describes the data; Section 3 explains the two approaches; Section 4 presents the copula model; Section 5 presents regression analysis; Section 6 summarizes results; Section 7 presents concluding remarks.

1.2 Data Description

1.2.1 China Sovereign CDS Market

Sovereign credit default swap contract performs similarly to an insurance against a future credit event of an obligation issued by a reference entity. Credit events that can trigger China sovereign CDS payments include failure to pay,[4] restructuring, and repudiation/moratorium. The restructuring clause for the China sovereign CDS contract is "full-restructuring." This means any bond with maturity up to 30 years can

[4]Unlike emerging European or Latin American sovereign CDS contracts, there is no grace period extension applicable to China sovereign CDSs in the case of failure to pay.

be considered as deliverable.[5] Typically, bonds issued by the Chinese government in the external markets and denominated in one of the "standard specified currencies" are considered as deliverable. The "standard specified currencies" are: U.S. dollar, Euro, Swiss franc, British pound, Canadian dollar and Japanese yen. China sovereign CDS started to trade with 100 and 500 bps fixed coupons from December 2009. The contract can roll into a new on-the-run twice a year on September 20 and March 20.[6] The final settlement is fixed as a cash settlement following the 2009 CDS "Big Bang" Protocol. The main advantage of cash settlement is that it reduces the potential for heightening the underlying bond market volatility caused by "naked" CDS buyers.[7]

China sovereign CDSs have become one of the most important sovereign CDS contracts since 2014. Table 1.1 Panel A shows the top three single-name sovereign CDSs in terms of the net notional outstanding amount[8] from 2013 to 2018. In 2013, the China sovereign CDSs contracts were the 9th largest single-name sovereign CDS contracts with a net notional amount outstanding around $7.42 billion. This amount almost doubled in 2014, which propelled it into third place. Augustin et al. (2016) show that domestic debt, international debt and GDP together can explain 75% of the cross country variation in net insured position. This can explain the other large net insured names shown in Table 1.1 Panel A. For instance, the Brazil sovereign CDS is one of the top insured names because it has the highest GDP amount among the other developing Latin America countries. China and South Korea are the two

[5]For China sovereign CDSs, the deliverable obligation characteristics are defined as: specified currency; not domestic currency; not domestic law; not domestic issuance; maturity up to 30 years; not subordinated; not sovereign lender; assignable loan; transferable; and not bearer. The deliverable obligation characteristics can be found in the International Swaps and Derivatives Association (ISDA) 2017 credit derivative physical settlement matrix.

[6]Rolling into a new contract is not mediatory. An old contract can remain and become off-the-run. There is still demand for those contracts, such as a 3.5 year CDS contract that matches a bond with similar maturity. Typically, trading volume is high the first couple of weeks after a new roll. Before December 2015, contracts could be rolled into a new on-the-run contract at four IMM dates: March 20, June 20, September 20, and December 20 each year. After December 2015, the roll dates have been modified into semi-annual.

[7]The "naked" CDS buyer needs to buy bonds from the market in the case of compulsory physical settlement. This action would drive up the bond price in the underlying cash market and heighten its volatility. In other words, the bond price will be temporarily driven above the expected recovery by the "naked" CDS buyers. This will cause a wealth transfer from the "naked" CDS buyers to the bondholders who do not hold CDS protection. This phenomenon is often referred as short squeezes.

[8]The weekly net notional amount of China sovereign CDSs outstanding are collected from DTCC. Figure A1.1 in the Appendix shows how trading in CDS contracts generates net notional amounts of CDSs outstanding in DTCC.

Table 1.1 – China Sovereign CDS Net Notional Amount Outstanding and Deliverable Bonds

Panel A: Rank and CDS Net Notional Amount Outstanding (Billion USD)						
Rank	2013	2014	2015	2016	2017	2018
1	19.057 (Italy)	20.272 (Italy)	17.852 (Italy)	17.066 (Italy)	14.432 **(China)**	13.356 **(China)**
2	16.080 (Brazil)	16.734 (Brazil)	12.724 (Brazil)	13.336 **(China)**	14.111 (Italy)	13.081 (Korea)
3	13.596 (Germany)	13.042 **(China)**	12.185 **(China)**	9.678 (Germany)	12.875 (Korea)	12.378 (Italy)
9	7.420 **(China)**	–	–	–	–	–
Panel B: Amount Outstanding: Deliverable Bonds versus Net Notional CDS (Billion USD)						
	2013	2014	2015	2016	2017	2018
Deliverable Bonds	1.672	0.283	0.200	0.200	2.200	5.200
Sovereign CDS	7.420	13.042	12.185	13.336	14.432	13.356

In this table, Panel A shows the net notional amount of China sovereign CDSs together with the net notional amount of the other top three net insured single-name sovereign CDS contracts from 2013 to 2018. We report the 2013 net notional outstanding amount separately since the China sovereign CDS was the 9th largest net insured sovereign CDS contract in that year. The weekly net notional amount outstanding is collected from the Depository Trust & Clearing Corporation (DTCC) and is denominated in billions USD. Data are expressed in average value and reported on a yearly basis. Panel B shows the China sovereign CDS's net notional amount outstanding versus the underlying end-of-year outstanding amount of deliverable bonds. The historical bond information is obtained from Bloomberg.

largest economies by size among the developing Asia Pacific countries.

While PIMCO suggested the increasing net notional amount of China sovereign CDSs is due to the rising concerns of the domestic banking system and slowing local economy, the default protection angle of trading China sovereign CDSs is weak according to the information revealed by deliverable bonds. Table 1.1 Panel B shows the underlying end-of-year outstanding amount of deliverable bonds. The historical bond information is collected from Bloomberg using debt distribution function. The deliverable obligation for China sovereign CDS can be both bonds and loans. We only include bonds since the lenders are supranational organizations such as the World Bank and the Asian Development Bank. They are considered a part of sovereign lenders, which makes those loans not deliverable. By the end of

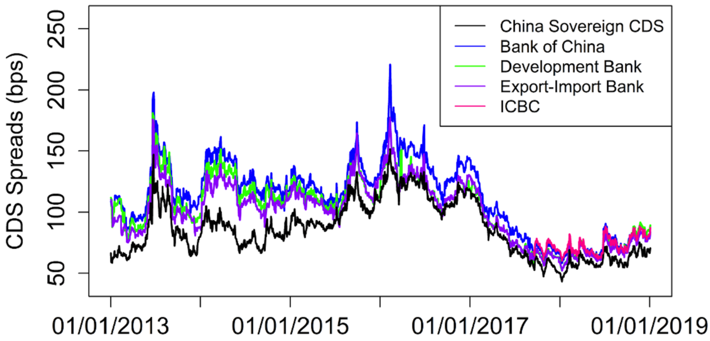
2018, the total outstanding of deliverable bonds was $5.2 billion. This only accounts for around 39% of net notional CDS amounts outstanding.

1.2.2 Relationship with Bank CDS

Figure 1.1 displays five-year daily China sovereign CDS spreads and CDS spreads of four Chinese Banks: two commercial banks (BoC, ICBC) and two policy banks (CDB, Chexim). China sovereign CDS spreads and bank CDS spreads are strongly co-moving. This feature holds for both commercial banks and policy banks. The strong co-movements of the China sovereign CDS spreads and the two commercial bank CDS spreads are expected, since Acharya et al. (2014) show bank CDS spreads and sovereign CDS spreads strongly co-move after a government bailout. The Chinese government started to bailout banks in 1998 due to the NPLs problem. In 1998, the Ministry of Finance (MOF) issued bank restructuring bonds worth $33 billion in order to recapitalize the "Big Four" by doubling their capital base.[9] A year later, the Chinese government established four state-sponsored asset-management companies to take over $169 billion of bad loans from the banks' balance sheet using debt-for-equity swaps. Despite all the rescue efforts, the amount of NPLs of the Big Four banks still amounted to around $300 billion by the end of 2003. In January 2004, the People's Bank of China (PBOC) injected 10% of total foreign currency reserves ($45 billion) into China Construction Bank and Bank of China. In the following year, the PBOC approved another restructuring plan for ICBC that cost over $80 billion and injected another $15 billion from foreign exchange reserves in order to write off the MOF's equity in the bank. Every effort was aimed at improving the banks' balance sheets and helping them to list their shares. Eventually, the NPL ratio (in terms of total loans) of China's banking sector decreased from 23.7% in 2002 to 8.6% in 2005 (Liu, 2009). The above bailout actions imply strong post-bailout co-movements of China sovereign CDS spreads and the two commercial bank CDS spreads. The co-movements in China sovereign CDS spreads and the two policy banks' CDS spreads are expected since policy banks are fully backed by the government.

[9]The Big Four banks in China are Industrial and Commercial Bank of China; Bank of China; Agricultural Bank of China; and China Construction Bank.

Figure 1.1 – China Sovereign CDS spreads versus Bank CDS spreads



This figure shows the five-year China sovereign CDS spreads versus the five-year CDS spreads of four Chinese Banks. The CDS data are collected from Credit Market Analysis (CMA) and sampled in daily frequency. For Bank of China, China Development Bank, and Export-Import Bank of China, the bank CDS data are from January 01, 2013 to November 23, 2018. For Industrial and Commercial Bank of China, bank CDS data are from September 15, 2017 to November 23, 2018.

1.2.3 The Data Set

The daily bid and ask quotes of five-year China sovereign CDSs are collected from CMA, which requires quotes from a minimum of three distinct sell side members for aggregation. It provides the end-of-day full curves for China sovereign CDSs at 5 p.m. New York time. We choose a five-year CDS contract so we could directly compare our regression results to the empirical findings in Eyssell et al. (2013), since they also use five-year China sovereign CDSs to perform their analysis. Daily bid and ask quotes of China sovereign CDSs are based on USD-denominated contracts. Mid-quotes are calculated as the average value of bid and ask. The time period covered is from January 01, 2013 to November 23, 2018.

We include four Chinese banks to study the relationship between sovereign and bank CDS spreads, including two commercial banks and two policy banks.[10] The two commercial banks are BoC and ICBC. BoC and ICBC were the world's largest

[10] We include these four banks also due to CMA CDS data availability. They are the only four Chinese banks which have CDS quotes during our sample period from January 01, 2013 to November 23, 2018.

and fourth largest banks by total assets in 2015 according to S&P global market intelligence report and they remained in these rankings in 2019. Moreover, BoC has been classified as a systemically important financial institution by FSB (Financial Stability Board) since 2011, and ICBC was added to the list in 2013. Therefore, both BoC and ICBC are important banks that can be used to represent the China banking system in terms of size and systemic importance.[11] The two policy banks are CDB and Chexim, both of which are heavily involved in the Belt and Road Initiative projects. For instance, both CDB and Chexim are stakeholders in the Silk Road Fund (SRF) established by the Chinese government in 2014. Since policy banks are fully backed by the government, we believe both banks can be good representatives of China policy bank system as well as the overall national power, especially from the view of foreign investors due to their business ties with oversea projects. We collected the daily bid and ask quotes of five-year BoC CDS, ICBC CDS, CDB CDS, and Chexim CDS from CMA. All contracts are denominated in USD. We calculate the mid-quote as the average value of bid and ask. The CDS data for all four banks are from January 01, 2013 to November 23, 2018 except ICBC. The data for ICBC CDS is avaliable from September 15, 2017 to November 23, 2018.

To study the determinants of daily China sovereign CDS spread changes, we use both local and global factors. Local factors include local stock market returns, bank stock returns, percentage changes in offshore exchange rates, percentage changes in ten-year China government bond yields, percentage changes in slope of yield curve, and percentage changes in VXFXI.[12] Local stock market returns are used as a proxy for the state of the domestic economy. Fontana and Scheicher (2016) and Blommestein et al. (2016) suggest the orthogonalized local stock market returns improve identification. Asian stock markets are highly affected by the overnight movements of the U.S. stock market; therefore, we improve the identification by using orthogonalized local stock market returns. The orthogonalization method was introduced in Dieckmann and Plank (2012). The orthogonalized series is constructed as the sum of intercept and residuals from a regression of local stock market returns

[11]We acknowledge the fact that both BoC and ICBC are large state-owned commercial banks, which may not represent those medium and small size banks. However, both banks are systemically important banks as reported by FSB. Therefore, we believe both of them play a more important role in affecting the Chinese banking system than those medium and small size banks.

[12]We also test the explanatory powers of three-month Shibor and seven-day repo rates. Neither of them is shown to be an important factor in our regression results.

on the lagged U.S. stock market returns. Local stock market returns are negatively related to the sovereign CDS spread changes, since a bullish local stock market indicates a strong economy, which is associated with a low sovereign CDS spread (Longstaff et al., 2011; Eyssell et al., 2013).

We include the VXFXI as the proxy for stock market volatility. Eyssell et al. (2013) use a close-to-close historical volatility estimator and find it to be a useless factor in explaining the daily China sovereign CDS spread changes. We improve the identification by considering implied volatility, which has been shown to have more explanatory power for credit spread than historical volatility (Cremers et al., 2008; Cao et al., 2010). To be specific, we utilize VXFXI, which applies VIX methodology to measure the market's expectation of the implied volatility of the U.S. traded iShares China Large-Cap ETF. We do not employ iVX (China's VIX) as the stock market volatility proxy for the following two reasons: 1) iVX index was launched at the end of 2016, which does not allow us to perform analysis for the 2013-3015 period; 2) iVX went dark on February 2018 (beginning of the U.S.−China trade war period) to halt market turbulence. We notice that VXFXI is highly correlated with VIX since it is based on the ETF traded in United States. To improve identification, we construct the orthogonalized percentage changes in VXFXI. It is constructed as the sum of intercept and residuals from a regression of percentage changes in VXFXI on the percentage changes in VIX.

We include the percentage changes of offshore exchange rate as one of the local factors. The effect of exchange rate is mixed. A strong domestic currency against the U.S. dollar indicates a healthy domestic economy, which is associated with a low credit spread. However, a strong currency also harms the economy by reducing exports. We use the offshore exchange rate based on executable quotes. Data are collected from Bloomberg using source Bloomberg Generic Price Executable (BNGE). The end-of-day BNGE bid and ask quotes are the executable bid and ask quotes at 5 p.m. New York time. Daily mid-quote of exchange rate is calculated as the average value of bid and ask. Collin-Dufresne et al. (2011) use both spot rate and slope as two possible determinants of corporate credit spread changes. A higher spot rate increases the risk neutral drift of the firm value process. It reduces the probability of default and further reduces the credit spreads (Longstaff and Schwatrz, 1995). We use China ten-year government bond yield as the spot rate proxy and the difference between China ten-year and two-year government bond yields as the proxy for the slope of yield curve following Collin-Dufresne et al. (2001). We include domestic bank stock returns as an additional local factor. Bank stock returns are the daily percentage changes in the self-constructed China bank index, which includes Hong Kong listed banks headquartered in mainland China. China bank stock returns are affected by the domestic stock market returns as well as the performance of overnight the U.S. bank stock market. We orthogonalized the domestic bank stock returns to improve identification. It is constructed as the sum of intercept and residuals from a regression of domestic bank stock returns on the lagged U.S. bank index returns and the orthogonalized local stock market returns.

Global factors include U.S. stock market returns, percentage changes in U.S. investment grade yield spreads, and percentage changes in high-yield spreads. U.S. stock market returns are the excess returns calculated as the MSCI USA index returns minus the risk-free rate.[13] Investment grade yield spreads are the yield spreads between S&P 500 BBB and S&P 500 AAA U.S. corporate bond indices. High-yield spreads are the yield spreads between S&P 500 BB and S&P 500 BBB U.S. corporate bond indices. We also include the change in Treasury yields, equity premium and VIX in our preliminary regression analysis.[14] However, multicollinearity problems occur when including those variables. Pearson's pairwise correlation coefficients for the full sample period are 0.95, -0.80 and -0.56 for the percentage changes in the equity premium and U.S. stock market excess returns pair, percentage changes in the VIX and U.S. stock market excess returns pair, percentage changes in the Treasury yield and percentage changes in the high-yield pair. Correlation coefficients are even higher in sub-periods. In fact, increasing U.S. equity returns imply a bull market with low volatility and high price-earning ratio. An increasing high-yield spread suggests a distressed economy with lower Treasury yield. We choose U.S. stock market returns and the percentage changes in U.S. high-yield spreads over the percentage changes in Treasury yields, equity premium, and VIX, since both of them have been shown to be the most important global factors in Longstaff et al. (2011).

[13]Data of risk-free rate are provided courtesy of Ken French. It is calculated as the daily linear interpolation of monthly one-month Treasury-bill return (from Ibbotson Associates).

[14]Treasury yields are the five-year constant maturity Treasury yields collected from the Federal Reserve Bank of St. Louis. Proxy for equity premium is the price-earnings ratio of S&P 100 index following Longstaff et al. (2011). VIX is the CBOE Volatility Index. Both time series are collected from Bloomberg.

Table 1.2 – Statistical Description

Panel A: Daily ΔLog(Sovereign CDS) and ΔLog(Bank CDS)					
	China SCDS	Bank of China	Development Bank	Export-Import Bank	ICBC
Mean	0.000	-0.000	-0.000	-0.000	0.000
Std.Dev	0.029	0.029	0.029	0.029	0.028
50^{th} percentile	-0.001	-0.001	-0.001	-0.001	-0.000
5^{th} percentile	-0.042	-0.042	-0.041	-0.041	-0.038
95^{th} percentile	0.048	0.045	0.041	0.041	0.048
Skewness	0.806	0.624	0.687	1.293	0.891
Excess Kurtosis	6.019	9.174	13.113	17.623	2.516
Jarque-Bera	0.000	0.000	0.000	0.000	0.000
Ljung-Box	0.316	0.001	0.002	0.000	0.893
LM	0.000	0.000	0.000	0.002	0.670
Pearson's ρ	-	0.550	0.451	0.463	0.725

Panel B: Covariates					
	Mean	Std.Dev	50^{th} percentile	5^{th} percentile	95^{th} percentile
Local Stock Return(%)	0.011	1.192	0.000	-1.923	1.819
ΔImplied Volatility(%)	-0.110	5.145	-0.515	-7.059	8.150
ΔFX(%)	0.006	0.247	0.001	-0.359	0.362
ΔGovt10yr(%)	0.000	0.037	0.000	-0.050	0.050
ΔSlope(%)	1.965	37.050	0.095	-21.143	24.635
Bank Stock Return(%)	0.027	1.494	-0.015	-2.269	2.390
U.S. Stock Return(%)	0.056	0.790	0.067	-1.313	1.269
ΔInvestment(%)	0.007	2.170	-0.009	-2.307	2.423
ΔHigh(%)	-0.030	2.735	-0.184	-3.768	4.471
ΔDebt/GDP	-0.000	0.001	0.000	-0.004	0.001
ΔReal Rate	-0.000	0.004	0.000	-0.005	0.006
ΔReserve/GDP	-0.002	0.003	-0.002	-0.008	0.005
ΔUncertainty($*10^{-3}$)	0.004	0.100	0.021	-0.159	0.160
ΔBudget/GDP	-0.000	0.012	-0.004	-0.014	0.026
ΔToT Volatility	0.000	0.001	0.000	-0.002	0.002
Equity Net Flow(billion USD)	-0.779	1.849	-0.713	-4.143	1.861
Bond Net Flow(billion USD)	1.234	4.943	1.654	-7.495	7.109

This table provides summary statistics on China sovereign and bank CDS spreads as well as local and global explanatory variables used in daily and monthly regression analyses. Each time series covers the period from January 2013 to November 2018 except ICBC CDS. The CDS spreads of ICBC are from September 15, 2017 to November 23, 2018. Panel A presents the summary statistics on daily changes in the logarithm of China sovereign and bank CDS rates. The p-values are reported for the Jarque-Bera test for the null of normality, the Ljung-Box test for the null of no autocorrelation up to 10 days, and the ARCH-LM test for the null of no volatility clustering up to 10 days. Panel B presents the summary statistics on explanatory variables used in daily and monthly regression analyses. Local Stock Returns are the daily percentage changes in the MSCI China index. ΔImplied Volatility is the daily percentage changes in the VXFXI. ΔFX is the daily percentage changes in offshore exchange rates expressed as units of Chinese Yuan per U.S. dollar. Δ Govt10yr is the daily percentage changes in the China ten-year government bond yields. ΔSlope is daily percentage changes in the yield spread between China ten-year and two-year government bond yields. Bank stock returns are the daily percentage changes in the self-constructed China bank index, which includes Hong Kong listed banks headquartered in mainland China. U.S. Stock Returns are the daily excess returns of MSCI USA index. ΔInvestment is the daily percentage changes in the yield spread between S&P 500 BBB corporate bond yield and S&P 500 AAA corporate bond yield. ΔHigh is the daily percentage changes in the yield spread between S&P 500 BB corporate bond yield and S&P 500 BBB corporate bond yield. ΔDebt/GDP is the monthly changes in China external debt over GDP ratio. ΔReal Rate is the monthly changes in China real interest rate. ΔReserve/GDP is the monthly changes in China foreign currency reserve over GDP ratio. ΔUncertainty is the monthly changes in China economic policy uncertainty Index. ΔBudget/GDP is the monthly changes in China government budget balance over GDP ratio. ΔToT Volatility is the monthly changes in 18-month rolling volatility of China terms of trades. Equity Net Flow is the monthly net new flows (inflows minus outflows) to long-term equity mutual funds. Bond Net Flow is the monthly net new flows (inflows minus outflows) to long-term bond mutual funds.

We include the monthly changes in real interest rate, external debt over GDP ratio, foreign currency reserve over GDP ratio, terms of trade volatility, government budget balance over GDP ratio, economic policy uncertainty, and equity and bond net flows as additional macroeconomic and investment-flow variables besides the local and global factors in the monthly regression analysis.[15] Those variables are commonly used in the literature (Eyssell et al., 2013; Dieckmann and Plank, 2012; Longstaff et al., 2011; Hilscher and Nosbusch, 2010). A higher real interest rate is related to a greater economic growth, which leads to a lower CDS spread. A high external debt level indicates a greater risk in repaying debt, which leads to a high CDS spread. A high foreign currency reserve ratio suggests a strong ability-to-pay, which leads to a low CDS spread. A high volatility of terms of trade means a high uncertainty in a country's ability to generate dollar revenue from exports. This implies a positive relationship between volatility of terms of trade and CDS spread. A negative government budget balance means government runs a budget deficit, which potentially leads to an increase in debt amount. A positively high government budget balance is associated with a low CDS spread. The China economic uncertainty index is a news-based index from Baker et al. (2016), which is used as a proxy for the policy-related economic uncertainty. A high economic uncertainty leads to a high CDS spread. Monthly bond and equity net flow (inflow minus outflow) data are collected from ICI indicating the net new cash flows into mutual funds, which focus on investing in global bond and equity markets. An positive net inflow can benefit the local economy by improving its access to global capital, which reduces the level of CDS spread. Macroeconomic variables are updated infrequently. We use linear interpolation to transform the quarterly updated variables into monthly frequency. We acknowledge that all the above macroeconomic variables can be classified as local factors. In our paper, we define those variables as the macroeconomic variables and only use them in the monthly regression analysis, as Eyssell et al. (2013) include those macroeconomic variables in daily regression analysis and find their coefficients

[15]We also include the monthly changes in terms of rade, current account balance over GDP ratio, general government international debt over GDP ratio, domestic debt over GDP ratio, as well as risk premium and term premium in our regression analysis. Risk premium is calculated following Longstaff et al. (2011) and Dieckmann and Plank (2012) as the spread between VIX and the Garman and Klass (1980) historical volatility estimator. We also use the volatility risk premium estimator from Bollerslev et al. (2011) as a robustness check, which yields similar results. Term premium is calculated using the monthly Fama-Bliss data from CRSP following Longstaff et al. (2011). None of them have explanatory powers. Results are provided in the Appendix.

are statistically significant with the wrong signs.

Table 1.2 Panel A provides the statistical description of the daily changes in the logarithm of China sovereign CDS and bank CDS rates. Both sovereign CDS returns and bank CDS returns are positively skewed. The pronounced excess kurtosis values suggest all series exhibit heavy tails. The linear serial dependence is tested by the Ljung-Box test with 10 lags. Most bank CDS returns have linear serial dependence. We use the Engle (1982) lagrange multiplier test for detecting ARCH effects. Results suggest the null hypothesis of no ARCH effect can be rejected at the 5% significant level for all series except ICBC.[16] Results from the Jarque-Bera test show the null hypothesis of normally distributed return is rejected at the 1% significant level for all series. Pearson's correlation coefficient ρ confirms the stylised positive association between China sovereign CDS returns and sovereign CDS returns. The correlation coefficient between sovereign CDS returns and commercial bank CDS returns is higher than the correlation coefficient between sovereign CDS returns and policy bank CDS returns. Table 1.2 Panel B provides the statistical description of all the explanatory variables used in daily and monthly regressions. The changes in local and global explanatory variables are measured as daily percentage changes. The changes in macroeconomic variables are calculated as monthly changes. Monthly equity and bond net flows data are directly obtained from ICI.

We observed some variables have low average returns and high volatility. For instance, Table 1.2 Panel B shows the daily returns of the local stock market has a high volatility compared to the mean. To be precise, the daily returns of the MSCI China index (taken in %) have a mean of 0.011 and a standard deviation of 1.192. This feature of low average returns and high volatility has been shown in other papers. For instance, Wang et al. (2011) shows the daily returns of MSCI China (taken in %) have a mean of 0.024 and a standard deviation of 1.481 from January 2000 to December 2009. Singh et al. (2013) shows the daily returns of MSCI China (taken in %) have a mean of 0.012 from January 1993 to December 2011, although they do not report the statistical description for standard deviation in their paper. To further check data accuracy, we collect the prices of MSCI China and re-produce the statistics. We confirm our statistical description of daily local stock returns is

[16]We use constant volatility as an alternative volatility model for ICBC CDS returns. The estimation results of marginal distribution, copula model, as well as goodness-of-fit are shown in the Appendix.

accurate.

We also notice the same feature of low average returns and high volatility for the daily returns of the FX rate. To be precise, the daily returns of the offshore exchange rate (taken in %) have a mean of 0.006 and a standard deviation of 0.247. This mean value is quite low compared to other spot FX rates. For instance, Christiansen et al. (2011) investigate the G10 currencies quoted against the U.S. dollar from January 1995 and December 2008. The average returns for the NZD (investment/lending currency) is 1.4% (annualized). However, this feature of low average returns and high volatility has been shown for the CNY/USD exchange rate in other papers as well. For instance, Kilic (2017) shows the daily returns of onshore CNY/USD exchange rate (taken in %) have a mean of 0.008 and a standard deviation of 0.159 from April 2004 to April 2011. There is one FX related event that happened during our sample period: the 2015 China exchange rate reform. PBOC announced on August 11, 2015 about the new CNY/USD central parity quoting mechanism. Under the new mechanism, banks must submit quotes that take the previous day's closing quotes into account, in conjunction with market demand and supply as well as the movements of other major currencies (Das, 2019). The announcement was also accompanied by an around 2% devaluation in the CNY/USD exchange rate. We delete the daily returns of the FX rate around the announcement date and find similar results. In fact, the 2015 China exchange rate reform happened during our second sub-period. Spot FX rate has been shown to have no explanatory power for the sovereign CDS spreads during this period. We noticed that our data have a similar mean value as Kilic (2017) but a slightly higher volatility. We further test whether the higher volatility might be due to the fact that we use offshore FX quotes rather than onshore quotes. To investigate this issue, we collect the onshore spot CNY/USD rate from Bloomberg and re-calculate the statistics. The daily returns of the onshore spot CNY/USD rate (taken in %) have a mean of 0.007, which is similar to the mean of offshore FX rate. The value of standard deviation is 0.195, which is lower. We use this onshore spot FX rate to re-produce our regression results shown in Table 1.7 Panel A, B, C &D column (8) and obtain similar results, although the significant level of the coefficient decreased from 1% to 5% for the third sub-period. We also check the data for accuracy by re-collecting the offshore exchange rate from Bloomberg and re-produce the statistics. We confirm our statistical description of daily spot FX returns is accurate.

The daily returns of the China ten-year government bond yield also have a small mean and a comparably high standard deviation. We manually delete the top 1% highest and the top 1% lowest returns of the China ten-year government bond yield from our sample. We re-estimate our model to test whether our regression results are driven by these returns. The regression results are similar to the ones shown in Table 1.7 Panel A, B, C &D column (5). In other words, we confirm that the China ten-year government bond yield has no explanatory power for China sovereign CDS spreads. We also test whether results hold after deleting more data, such as the top 2% highest and the top 2% lowest returns of the China ten-year government bond yield. Again, the results show that the China ten-year government bond yield is not an important factor for China sovereign CDS pricing.

1.3 Modelling Framework: Two Approaches

We use two approaches in this paper: the copula model and regression analysis. Both methods are used to answer different research questions. First, copula model is used to study the joint extreme movements of China sovereign CDS spreads and bank CDS spreads by measuring the tail dependence coefficient. The copula model can capture a more complete dependence structure in a joint return distribution framework that a linear correlation cannot fully describe (Meine et al., 2016). Second, time series regression is used to study the determinants of China sovereign CDS spread changes.

1.3.1 Copula: Modelling Extreme Co-movements

The joint extreme co-movements of sovereign and bank CDS spreads can be captured by the copula model implied tail dependence coefficient. We use both dynamic and static copulas in this paper. The advantage of using the copula model is that it allows us to study the probability of simultaneous large increases in both sovereign and bank credit risks. Using the copula model to study the dependence structure is also used in other fields, such as the energy and stock market literatures as well. For instance, Reboredo (2011) uses the tail dependence coefficient of crude oil pairs from January 1997 to June 2010 and finds the existence of high tail dependence, which indicates the oil market is "one great pool." Chollete et al. (2011) study the tail dependence coefficient of fourteen national stock market indices of G5, East Asia, and Latin American countries from January 1990 to May 2006. They find that the dependence increased over time and that there are international limits to diversification. We are the first, to our best knowledge, to study the co-movements of the China sovereign and bank CDS spreads using the copula model. The detailed description about the copula model, estimation method, goodness-of-fit, tail dependence coefficient, and rank coefficient is illustrated in Section 1.4.

1.3.2 Regression Analysis

We use time series regression to study the determinants of China sovereign CDS spread changes following the previous sovereign CDS literature (Longstaff et al., 2011; Eyssell et al., 2013; Dieckmann and Plank, 2012; Fontana and Scheicher, 2016). We perform regression analyses in both daily and monthly frequencies. For the daily time series regression, we include the commonly used local and global factors as well as additional local factors. To be specific, we include both offshore exchange rate and implied volatility as two additional local factors, which were not included in Eyssell et al. (2013). We perform daily regression analysis for each of the four sub-periods. Those four sub-periods are identified by applying the Bai and Perron (2003) structural break test on China sovereign CDS returns. Our goal is two-fold: 1) we try to find the important factors for China sovereign CDS spreads; 2) we want to test whether local variables become more important in explaining the sovereign CDS spread changes in a crisis period, such as the U.S.–China trade war period. However, we do not include bank CDS returns as one of the local factors in our time series regression for the following two reasons: first, it is typically not used in the sovereign CDS literature as one of the factors in studying sovereign CDS spread changes; and second, we might need to address the endogeneity issue when including this variable in regression analysis. Kallestrup et al. (2016) suggest sovereign CDS and bank CDS spreads might be determined jointly, and there is a possibility of endogeneity of bank CDS premia. To address the endogeneity issue, we need an instrument for bank CDS returns. However, finding a good instrument is a difficult task. Kallestrup et al. (2016) test the bank's leverage as the instrument for bank CDS returns and finds it to be a weak instrument. Based on the above two reasons, we do not include bank CDS returns in our regression analysis. Still, we provide the estimation results of the regression, which includes bank CDS returns as one of the local factors in the Appendix. The detailed description about the regression model is stated in Section 1.5. The monthly time series regression is used to test the explanatory power of macroeconomic and investment-flow variables after controlling for the local and global variables. We perform only the monthly regression analysis for the full sample period due to limited sample size.

1.4 Copula Model

1.4.1 Marginal Distribution

The daily changes in the logarithm of CDS spreads, denoted as r_t, is specified by either ARMA(p,q)-GARCH(1,1)-skT or ARMA(p,q)-EGARCH(1,1)-skT model. The optimal (p,q) combination with p∈[0,10] and q∈[0,10] is selected using the Akaike Information Criterion (AIC). The EGARCH(1,1) model incorporates the asymmetric volatility. $\gamma < 0$ suggests volatility increases more in response to a negative shock than to a positive shock. The selection of conditional volatility model is based on two criteria: AIC and significance of leverage coefficient at the 5% significance level. The filtered standardised residuals are assumed to follow a Hansen (1994) skewed t distribution. It has two "shape" parameters: asymmetry parameter denoted as ζ and degrees of freedom parameter denoted as ν>2. The model collapses to standardized Student's t distribution when the skewness parameter ζ equals to 0. It becomes skewed Normal distribution when ν goes to infinity. We recover Normal distribution when ζ equals to 0 and ν goes to infinity. The generalized form of ARMA(p,q)-GARCH(1,1)-skT and ARMA(p,q)-EGARCH(1,1)-skT models are as follows:

$$r_t = a_0 + \sum_{i=1}^{p} a_i r_{t-i} + \varepsilon_t + \sum_{j=1}^{q} b_j \varepsilon_{t-j} \tag{1.1}$$

GARCH(1,1) model

$$\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + \alpha\varepsilon_{t-1}^2 \tag{1.2}$$

EGARCH(1,1) model

$$\log(\sigma_t^2) = \omega + \beta\log(\sigma_{t-1}^2) + \alpha\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right) \tag{1.3}$$

where a_0 and ω are constants; a_p and b_q are the parameters of AR lag p and MA lag q; β and α are the parameters of GARCH(1) and ARCH(1) components; γ measures the scale of asymmetric volatility. A positive γ suggests volatility increases more in response to a positive shock than to a negative shock. The Uniform(0,1) variable is obtained through the probability integral transformation $u = F(x)$, where $F(\cdot)$ is the skewed Student's t cumulative distribution function.

1.4.2 Copula Function

Dependence structure is investigated using both static and dynamic copula models. The dependence structure is modelled conditionally in the dynamic context. Copula models allow us to measure the tail dependence. The lower and upper tail dependence coefficients help us to measure the tendency of two assets' prices to jump or crash together. We include two Elliptical copulas: Gaussian copula and Student's t copula as well as two Archimedean copulas: Gumbel copula and Symmetrised Joe-Clayton copula. Gaussian copula is included as the natural benchmark. Gumbel copula is used to investigate the upper tail dependence. The Student's t and SJC[17] copulas consider both upper and lower tail dependence. The detailed description of copula functions are shown in the Appendix.

[17]The SJC copula is a modification of the original Joe-Clayton copula, which allows upper and lower tail dependence and symmetric dependence as a special case when $\lambda^U = \lambda^L$.

The conditional dependence structure of two CDS series may vary through time. Following Patton (2013), Figure 1.2 shows the rolling rank correlations between the standardized residuals for China sovereign CDS and four Chinese bank CDSs over a 90-day moving window. All time series cover the period from January 01, 2013 to November 23, 2018 except ICBC. ICBC CDS data are only avaliable from September 15, 2017 to November 23, 2018. The rank correlation between the standardized residuals of China sovereign CDS and BoC CDS started to rise in mid-2016. It hovered around 0.43 from 2013 to mid-2016, then rose to around 0.73 in 2017-2018. The rank correlation between the standardized residuals of China sovereign CDS and CDB CDS also rose from around 0.36 in 2013-2016 to around 0.53 in 2017-2018. These dynamic correlation features suggest we should consider time-varying copula models.

We consider two types of dynamic copulas in this paper. The first type follows Patton (2006), which sets the foundation of dynamic copula models. The time-varying dependence structure adopts a ARMA(1,m) process as follows:

$$\gamma_t = \Lambda(\omega + \varphi\gamma_{t-1} + \psi\Gamma_t) \tag{1.4}$$

$$where \quad \Gamma_t = \begin{cases} \frac{1}{m}\sum\limits_{j=1}^{m}\Phi^{-1}(u_{1,t-j})\Phi^{-1}(u_{2,t-j}) & Gaussian \\ \frac{1}{m}\sum\limits_{j=1}^{m}t_v^{-1}(u_{1,t-j})t_v^{-1}(u_{2,t-j}) & Student's\ t \\ \frac{1}{m}\sum\limits_{j=1}^{m}|u_{1,t-j}-u_{2,t-j}| & Gumbel\ and\ SJC \end{cases}$$

This function permits mean-reversion in the dependence measure of interest γ. We set m=10 following Patton (2006) and Fei et al. (2017). Φ^{-1} is the inverse of univariate standard normal distribution function. t_v^{-1} is the inverse of Student's t distribution function with $v > 2$ degree of freedom. γ_t refers to the ρ_t for Gaussian and Student's t copulas. For Gumbel copulas, γ_t stands for δ_t. For SJC copula, γ_t stands for both τ^U and τ^L. Λ takes different forms for different copulas. For the elliptical copula(Gaussian and Student's t), $\Lambda(y) = tanh(y/2) = (1-e^{-y})(1+e^{-y})^{-1}$ takes the modified logistic transformation to ensure $\rho_t \in (-1,1)$. For the Gumbel copula, $\Lambda(y) = 1+e^{y}$ to ensure $\delta_t \in (1,\infty)$. For the SJC copula, $\Lambda(y) = (1+e^{-y})^{-1}$ to ensure λ^U and $\lambda^L \in (0,1)$.

The second type of dynamic copula follows the GAS(1,1) model from Patton (2013) and Creal et al. (2013). It is a generalized autoregressive score model. The time-varying parameter δ_t is first mapped into f_t using a strictly increasing transformation:

$$f_t = h(\delta_t) \Leftrightarrow \delta_t = h^{-1}(f_t) \tag{1.5}$$

Similarly, $\delta_t = 1 + exp(f_t)$ to ensure $\delta_t \in (1,\infty)$ for the Gumbel copula. For the Gaussian and Student's t copula, δ_t refers to ρ_t. The function $\delta_t = (1 - exp(-f_t))/(1 + exp(-f_t))$ is used to ensure $\delta_t \in (-1,1)$. The degrees of freedom parameter in the Student's t copula is assumed to be constant. The dynamic of f_{t+1} is modelled as a function of f_t and a "forcing variable" s_t , which is related to the standardized (scaled) score of copula log-likelihood. The formula is shown as:

$$f_{t+1} = \omega + \beta f_t + \alpha s_t \tag{1.6}$$

$$where \qquad s_t = S_t \cdot \nabla_t \tag{1.7}$$

$$\nabla_t = \frac{\partial}{\partial \delta} \log c(U_{1t}, U_{2t}; \delta_t) \tag{1.8}$$

$$S_t = I_t^{-1/2} = I(\delta_t)^{-1/2} \tag{1.9}$$

S_t is the scaling function which takes the form as $I_t^{-1/2}$, where $I_t = E_{t-1}[\nabla_t \nabla_t'] = I(\delta_t)$. Creal et al. (2013) suggest using the score for updating f_t defines a steepest ascent direction for improving model's local fit in terms of likelihood or density at time t given the current position of parameter f_t. Once the set $[\omega, \beta, \alpha]$ is estimated, we obtain the specified time-varying f_t. Then, we use f_t to calculated the dynamics of δ_t.

1.4.3 Estimation and Goodness-of-Fit

Parameters are estimated using a two-stage process (e.g., Fei et al., 2017; Patton, 2013; Reboredo, 2011). First, we estimate the parameters of the marginal distributions. Second, we estimate the parameters of copula models conditional on the margins. The log-likelihood function takes form as:

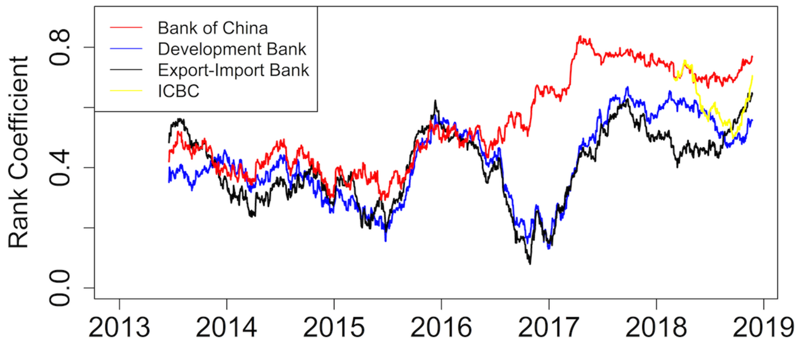
$$\mathcal{L}(\theta_1, \theta_2, \alpha) = \sum_{t=1}^{T} lnc[F(x_t;\theta_1), G(y_t;\theta_2);\alpha] + \sum_{t=1}^{T} lnf(x_t;\theta_1) + \sum_{t=1}^{T} lng(y_t;\theta_2) \tag{1.10}$$

where θ_1, θ_2 are the parameters for the marginal distributions. The second stage ML estimation can be expressed as finding the α=arg $\underset{\alpha}{max} \sum_{t=1}^{T} lnc[\hat{u}_{1,t}, \hat{u}_{2,t};\alpha]$, where $\hat{u}_{1,t} = F(x_t;\hat{\theta}_1)$ and $\hat{u}_{2,t} = G(y_t;\hat{\theta}_2)$. The two-step ML estimator of copula parameters is asymptotically normal and consistent. Although it is not efficient, the simulation results from Joe (2005) and Patton (2006) shows that the efficiency loss is generally small in practice.

We use different methods to evaluate the goodness-of-fit of the marginal distribution. The Ljung-Box test is used to test whether the persistence in CDS returns has been accounted. P-value of LB(10) test higher than 0.05 means the null hypothesis that the residuals from ARMA(p,q) are not autocorrelated at lag 10 cannot be rejected at the 5% significant level. Engle (1982) Lagrange multiplier test is employed to test whether volatility clustering has been accounted. P-value of LM(10) test higher than 0.05 means the null hypothesis that there is no ARCH effect at lag 10 cannot be rejected at the 5% significant level. Diebold et al.(1998) suggests that û should be i.i.d. uniform(0,1) distributed if marginal distribution is correctly specified. This is tested in two steps: first, we use LB statistic[18] to exam the serial correlation of the first four

[18]Patton(2006) and Reboredo(2011) use the LM statistic to exam the serial correlation of the first four moments. It is defined as (T-h)R^2, where h=20 and R^2 is the coefficient of determination for the

Figure 1.2 – Spearman's Rank Correlation Coefficients



This figure shows the spearman's rank correlation coefficients between the standardized residuals of China sovereign CDS and bank CDSs over a 90-day moving window.

moments of $(\hat{u}\text{-}\bar{u})^j$, j∈{1,2,3,4} (see Fei et al., 2017); and second, we use the Cramér-von Mises test to evaluate whether the transforms are Uniform(0,1) distributed.[19] We accept i.i.d. and uniform assumptions if the LB test and CvM tests cannot be rejected at the 5% significant level. We use AIC to select the best copula model (Fei et al., 2017; Reboredo, 2011; Atil et al., 2016) and then perform a goodness-of-fit test on the selected copula. Following Patton (2013), we use bootstrap standard errors (m=1,000) for copula parameters. The bootstrap standard errors use a block bootstrap[20] of the original returns and estimation of all stages on the bootstrap sample. The goodness-of-fit test is a traditional specification seeking to determine whether the selected copula is different from the (unknown) true copula (Patton, 2013). Cramér-von Mises test is used for measuring goodness-of-fit.[21] It uses the empirical copula

regression. It is distributed as χ^2(h) under the null of serial independence. A p-value higher than 0.05 suggests the i.i.d. assumption cannot be rejected at the 5% level. We employ this method as an alternative measurement and the p-values are higher than 0.05 for all series.

[19]We also employ the Kolmogorov-Smirnov and Anderson-Darling tests to evaluate whether the transforms are Uniform(0,1) distributed. Results of both tests show that we cannot reject the U(0,1) assumption at the 5% significant level.

[20]The stationary bootstrap with an average block length of 60 observation is used following Patton (2013). The data for the ICBC CDS and China sovereign CDS pair covers much shorter period. We use a block-length selection method from Patton et al. (2009) to determine the optimal block size.

[21]We also use the KS test for the robustness test of goodness-of-fit. The simulation based (s=200) p-values of KS tests for all the selected copula models are above 0.05. This is consistent with the CvM

$\hat{C}_T$, which is defined as $\hat{C}_T(u)=\frac{1}{T}\sum_{t=1}^{T}\prod_{i=1}^{n}1(\hat{U}_{it}\leq u_i)$. The CvM tests for static copula is defined as $CvM_C = \sum_{t=1}^{T}[C(U_t;\hat{\theta}_T) - \hat{C}_T(U_t)]^2$. The true conditional copula is estimated by the empirical copula. The time-varying true conditional copula requires a "Rosenblatt" transform of the data. The transformation in bivariate case is $V_{1t} = U_{it}\forall$t and $V_{2t} = C_{2|1,t}(U_{2t}|U_{1t};\theta)$, where $C_{2|1,t}$ is the conditional distribution of $U_{2t}|U_{1t}$. The empirical copula of the estimated "Rosenblatt" transform is $\hat{C}_T^v(v)=\frac{1}{T}\sum_{t=1}^{T}\prod_{i=1}^{n}1(\hat{V}_{it}\leq v_i)$. The CvM test for time-varying copula is defined as $CvM_R = \sum_{t=1}^{T}[C^v(V_t;\hat{\theta}_T) - \hat{C}_T(V_t)]^2$, where $C^v(V_t;\hat{\theta}_T)=\prod_{i=1}^{n}V_{it}$. The simulated-based p-value for CvM GoF test statistic is produced using the following steps: (1) estimate the marginal distribution and copula model parameters $\hat{\theta}_T$ on the actual data; (2) compute the CvM (GoF) test statistic $\hat{G}_T$ on the actual data; (3) simulate a time series of same length T as actual data from the model using the estimated parameter $\hat{\theta}_T$; (4) estimate the model on the simulated data to obtain the parameter estimate $\hat{\theta}_T^s$; (5) compute the CvM (GoF) statistic $\hat{G}_T^s$ on the simulated data; (6) repeat steps (3)-(5) S=200 times;[22] (7) compute the simulated-based p-value as $p_{T,S} = \frac{1}{S}\sum_{s=1}^{S}1(\hat{G}_T^s \geq \hat{G}_T)$. Please see Patton (2013) for a detailed description.

1.4.4 Tail Dependence Coefficient and Rank Coefficient

We use two copula model implied correlation measures to quantify dependence. First, the tail dependence coefficient λ^U and λ^L, which measures the asymptotic likelihood that two variables go up or down at the same time (Chollete et al., 2011). It can be seen as the conditional probability of an extreme event beyond some threshold u when u approaches some limits as 0 or 1.[23] The upper tail dependence coefficient λ^U looks at the probability that U exceeds the u-quantile $F_U^{-1}(u)$ given that V exceeds the u-quantile $F_V^{-1}(u)$. λ^U measures the limit of this conditional probability when u goes to 1. The tail dependence coefficient λ^U=0.3 reads as X and Y series are asymptotically dependent in upper tail with the strength of dependence as 0.3. The Gaussian copula has a zero tail dependence coefficient. The Student's t copula has

test result and indicates that we cannot reject the selected copula model at the 5% significant level for all pairs.

[22]We do not pursue a higher number of simulations because 1) the p-value remains stable after s=100; 2) each 100 simulations takes around 25 hours.

[23]For example, u approaches 0 gives lower/left tail dependence coefficient, which measures the limit of downside risk as losses becomes extreme.

Table 1.3 – Estimation Results of Marginal Distribution and Goodness-of-Fit

Panel A: Marginal Distribution							
	Mean	Variance				Skew T	
	a_0	ω	β	α	γ	v	ζ
January 01, 2013 *to November* 23, 2018							
China Sovereign CDS	0.0000 (0.0002)	-0.4920^{**} (0.0878)	0.9327^{**} (0.0123)	0.2389^{**} (0.0181)	0.0391^{**} (0.0119)	5.5536^{**} (0.6069)	0.1660^{**} (0.0312)
Bank of China	−0.0000 (0.0003)	-0.8270^{**} (0.1039)	0.8814^{**} (0.0145)	0.3089^{**} (0.0215)	0.0438^{**} (0.0138)	3.4274^{**} (0.1596)	0.0741^{**} (0.0253)
Development Bank	−0.0001 (0.0014)	-0.7969^{**} (0.1290)	0.8869^{**} (0.0179)	0.1520^{**} (0.0150)	0.0917^{**} (0.0123)	3.1896^{**} (0.1208)	0.0657^{**} (0.0252)
Export-Import Bank	−0.0000 (0.0002)	0.0003 (0.0000)	0.4140^{**} (0.0587)	0.1615^{**} (0.0189)	–	3.2612^{**} (0.1329)	0.0860^{**} (0.0251)
September 15, 2017 *to November* 23, 2018							
China Sovereign CDS	0.0009 (0.0016)	0.0001 (0.0000)	0.8199^{**} (0.0875)	0.0858^{*} (0.0408)	–	7.9253^{**} (3.0119)	0.2230^{**} (0.0705)
ICBC	0.0008 (0.0016)	0.0001 (0.0001)	0.8173^{**} (0.1293)	0.0499 (0.0301)	–	5.0590^{**} (1.0631)	0.2215^{**} (0.0728)

Panel B: Goodness-of-Fit							
	$LB(10)$	$LM(10)$	$m1$	$m2$	$m3$	$m4$	CvM
January 01, 2013 *to November* 23, 2018							
China Sovereign CDS	0.8872	0.6137	0.8141	0.7401	0.8249	0.6414	0.6340
Bank of China	0.9565	0.8002	0.5850	0.4963	0.9360	0.5991	0.4176
Development Bank	0.7720	0.9356	0.1669	0.2485	0.2671	0.4461	0.7372
Export-Import Bank	0.9606	0.5562	0.8029	0.6344	0.8762	0.6690	0.4823
September 15, 2017 *to November* 23, 2018							
China Sovereign CDS	0.1803	0.8268	0.3407	0.7618	0.4437	0.6617	0.9251
ICBC	0.9131	0.9882	0.9565	0.7716	0.9169	0.8216	0.8421

This table reports the estimated parameters of marginal distribution defined in (eq(1.1)-eq(1.3)). Standard errors are reported in parentheses. Standardized residuals are checked for autocorrelation and ARCH effect using Ljung-Box test and Engel's LM test at lag10. The first four moments of $(\hat{u}\text{-}\bar{u})^j$ are used to check for i.i.d. assumption. m1, m2, m3, and m4 stand for the p-values of Ljung-Box test on the first four moments of $(\hat{u}\text{-}\bar{u})^j$ at lag10. The null hypothesis of uniform(0,1) distributed U is tested using Cramér-von Mises test. ** and * denote significance at the 1% and 5% level, respectively.

symmetric tail dependence, which means the upper tail dependence coefficient equals the lower tail dependence coefficient. The Gumbel copula has upper tail dependence but zero lower tail dependence. The SJC copula has asymmetric tail dependence. Second, the implied Kendall's τ rank correlation coefficient.[24] It is a coefficient that represents the degree of concordance between two ranked variables. Our main interest is the tail dependence coefficient. The closed-form expressions for Kendall's τ, λ^U and λ^L of Gaussian, Student's, Gumbel and SJC copulas are shown in the

[24]The rank correlation coefficient measures the dependence of the ranks. It is more robust than the traditional Pearson's correlation coefficient ρ. The rank correlation is especially useful when analysing series with outliers, since it depends only on the rank rather than the level.

Appendix.

1.5 Regression

We study the determinants of five-year China sovereign CDS spread changes using time series regression. Our analysis uses the changes in the natural logarithm of sovereign CDS rates following Acharya et al. (2014). We make this choice to reduce the impact of outliers. We perform the regression analyses in both daily and monthly frequencies. The daily regression is specified as:

$$\Delta Log(CDS)_t = \alpha + \Delta X_{1,t}^T \beta + \Delta X_{2,t}^T \gamma + \varepsilon_t \tag{1.11}$$

Vector $\Delta X_{1,t}$ includes the change in global factors, such as U.S. stock returns; the daily percentage changes in U.S. investment grade; and the daily percentage changes in high-yield spreads. The U.S. investment grade yield spread is the calculated as the yield spread between S&P 500 BBB corporate bond yield and S&P 500 AAA corporate bond yield. U.S. high-yield spread is calculated as the yield spread between S&P 500 BB corporate bond yield and S&P 500 BBB corporate bond yield. Vector $\Delta X_{2,t}$ includes the change in local factors, such as orthogonalized local stock market returns; orthogonalized percentage changes in the VXFXI; orthogonalized bank stock returns; percentage changes in offshore exchange rates; percentage changes in China ten-year government bond yields; and percentage changes in slope. Slope is measured as the yield spread between China ten-year and two-year government bond yields.

Four sub-periods are identified by the Bai and Perron (2003) structural break test on China sovereign CDS returns: 1) pre-stock market turbulence period from January 01, 2013 to September 05, 2014; 2) stock market turbulence period from September 08, 2014 to February 11, 2016;[25] 3) the post-stock market turbulence period from

[25]Chinese stock market was on a roller coaster ride during this period. The stock market bubble started at around mid-2014 and crashed in mid-June 2015. The MSCI China index lost around 20% of its value from June 12, 2015 to July 8, 2015, while the onshore Shanghai composite index lost 32% of its value over the same period (Sornette et al., 2015). The MSCI China index reached its bottom at around February

February 12, 2016 to January 05, 2018; 4) U.S.-China trade war period from January 08, 2018 to November 23, 2018.[26]

The monthly regression analysis allows us to test whether macroeconomic and investment-flow variables have explanatory power for the monthly China sovereign CDS spread changes. The monthly regression is specified as:

$$\Delta Log(CDS)_t = \alpha + \Delta X_{1,t}^T \beta + \Delta X_{2,t}^T \gamma + \Delta X_{3,t}^T \theta + \varepsilon_t \tag{1.12}$$

Vector $\Delta X_{1,t}$ and $\Delta X_{2,t}$ represent the same local and global variables as in eq(1.11) but in monthly frequency. Vector $\Delta X_{3,t}$ includes the monthly changes in macroeconomic and investment-flow variables. To be specific, it includes the monthly changes in China external debt over GDP ratio, real interest rate, foreign currency reserve over GDP ratio, economic policy uncertainty, government budget balance over GDP ratio, 18-month rolling volatility of China terms of trades and the ICI equity and bond net flows. We also test the explanatory powers of the monthly changes in terms of trade, current account balance over GDP ratio, general government international debt over GDP ratio, domestic debt over GDP ratio, as well as risk premium and term premium. The coefficients on all these variables are statistically insignificant. The regression results are shown in the Appendix. We perform a monthly regression analysis for the full sample only due to limited time-series data.

2016.

[26]The U.S.-China trade war between China and the United States began in January 2018 when the U.S. announced tariffs on imported washing machines and solar panels. The latter affected China the most. Correspondingly, China sovereign CDS spreads started to increase from January 2018. Moreover, the president of United States signed an executive memorandum to impose retaliatory tariffs on up to $60 billion in Chinese imports on March 22, 2018. This signaled the deepening U.S.-China trade war.

1.6 Results

1.6.1 Marginal Distribution Models

Table 1.3 reports the ML estimates for the marginal distributions. The d.o.f parameter v has a smaller value for bank CDS returns than for sovereign CDS returns. This suggests bank CDS returns have fatter tails. The skewness parameter ζ is positively significant for all series. This indicates both bank and sovereign CDS returns are right/positively skewed. The p-values of the Ljung-Box and Engel's LM tests suggest neither autocorrelation nor ARCH effects remain in the standardized residuals. The p-values of the serial independence LB test on the first four moments of the estimated probability integral transformations $(\hat{u}-\bar{u})^j$, $j \in \{1,2,3,4\}$ are all above 0.05. This suggests the i.i.d. assumption cannot be rejected at the 5% significant level for all series. The p-values of CvM tests indicate the null hypothesis that the transforms are Uniform(0,1) cannot be rejected at the 5% significant level for all series. Overall, the goodness-of-fit results show our marginal distribution models are not misspecified and the copula models can correctly capture the co-movement between different return series.

1.6.2 Copula Models

Table 1.4 reports the results of AIC and goodness-of-fit for static, dynamic ARMA and dynamic GAS copulas. There are several conclusions we can draw from the estimation results. First, the relationship between China sovereign CDS returns and bank CDS returns is best captured by the dynamic copula models. In fact, three out of four sovereign-bank CDS pairs choose the GAS copula model. Second, the Student's t copula out-performs other copula models, which suggests symmetric tail dependence coefficients for all pairs. This is consistent with the findings in Atil et al. (2016) and Fei et al. (2017). Atil et al. (2016) studies the relationship between U.S. and EU sovereign CDS spreads and shows Student's t copula is the preferred model for most countries. Fei et al. (2017) shows the dynamic dependence between the Europe, Auto, and Financial iTraxx CDS indices and their corresponding Stoxx equity indices during the financial crisis period are best captured by ARMA type Student's t copula. The p-values of CvM tests indicate we cannot reject the

Table 1.4 – Static and Dynamic Copulas: AIC and Goodness-of-Fit

Copula Formulation	AIC (Log_Likelihood)	Bank of China	Development Bank	Export-Import Bank	ICBC
Panel A: Static Copula					
Gaussian (*Static*)	AIC (LL)	−573.94 (287.97)	−334.24 (168.12)	−314.42 (158.21)	−202.38 (102.19)
Gumbel (*Static*)	AIC (LL)	−616.36 (309.18)	−343.00 (172.50)	−325.46 (163.73)	−205.66 (103.83)
Student's t (*Static*)	AIC (LL)	−687.60 (345.80)	−354.62 (179.31)	−333.62 (168.81)	−233.62 (118.81)
SJC (*Static*)	AIC (LL)	−636.00 (320.00)	−347.86 (175.93)	−325.58 (164.79)	−222.72 (113.36)
Panel B: Dynamic Copula					
Gaussian (*ARMA*)	AIC (LL)	−592.34 (299.17)	−337.72 (171.86)	−318.62 (162.31)	−211.88 (108.94)
Gumbel (*ARMA*)	AIC (LL)	−693.06 (349.53)	−341.94 (173.97)	−327.46 (166.73)	−229.12 (117.56)
Student's t (*ARMA*)	AIC (LL)	−699.54 (353.77)	−353.90 (180.95)	**-334.26** **(171.13)**	−252.04 (130.02)
SJC (*ARMA*)	AIC (LL)	−748.80 (380.40)	−351.04 (181.52)	−323.84 (167.92)	−241.80 (126.90)
Gaussian (*GAS*)	AIC (LL)	−690.50 (348.25)	−350.42 (178.21)	−322.42 (164.21)	−232.56 (119.28)
Gumbel (*GAS*)	AIC (LL)	−733.60 (369.80)	−358.34 (182.17)	−331.70 (168.85)	−244.16 (125.08)
Student's t (*GAS*)	AIC (LL)	**-785.18** **(396.59)**	**-368.02** **(188.01)**	−332.60 (170.30)	**-266.66** **(137.33)**
Panel C: Goodness-of-Fit					
CvM		0.310	0.845	0.460	0.390

This table reports AIC and goodness-of-fit of static and dynamic copulas for sovereign-bank CDS pairs. Each sovereign-bank CDS pair is represented using the bank's name. Copula models include Gaussian copula, Gumbel copula, Student's t copula, and Symmetrised Joe-Clayton copula. Dynamic copulas include both ARMA and GAS types. AIC is the Akaike information criterion and LL is the maximized log-likelihood. Copula model selection is based on AIC. For each sovereign-bank CDS pair, bold font denotes the selected copula formulation overall. Simulation-based (s=200) p-value of CvM test is performed for the selected copula formulation of each sovereign-bank pair.

Table 1.5 – Estimation Results of Static and Dynamic Student's t copula

	Static		ARMA				GAS			
	ρ	v	ω	ψ	φ	v	ω	α	β	v^{-1}
Bank of China	0.582^{**} (0.047)	3.643^{**} (0.803)	−0.366 (0.214)	0.006 (0.028)	2.908^{**} (0.391)	3.644^{**} (0.834)	**0.031** (0.057)	**0.117*** (0.049)	**0.979**** (0.037)	**0.278**** (0.053)
Development Bank	0.440^{**} (0.033)	9.126^{**} (2.795)	−0.084 (0.388)	0.018 (0.068)	2.320^{*} (0.902)	9.941^{**} (2.485)	**0.004** (0.111)	**0.021** (0.026)	**0.995**** (0.119)	**0.092**** (0.027)
Export-Import Bank	0.430^{**} (0.025)	9.842^{**} (2.282)	**-0.037** (0.254)	**0.031*** (0.015)	**2.191**** (0.596)	**10.510**** (2.307)	0.920^{**} (0.096)	0.093^{*} (0.043)	0.000 (0.057)	0.097^{**} (0.020)
ICBC	0.706^{**} (0.054)	2.199^{**} (0.874)	3.167^{**} (0.927)	0.185^{**} (0.070)	-2.792^{*} (1.075)	2.375^{**} (0.648)	**0.496** (0.532)	**0.582**** (0.108)	**0.705**** (0.243)	**0.446**** (0.044)

This table shows the ML estimation results of Student's t copula models in static, dynamic ARMA, and dynamic GAS formulations. Each sovereign-bank CDS pair is represented using the bank's name. For each sovereign-bank CDS pair, bold font denotes the ML estimation results of the selected copula formulation overall. The numbers in parentheses are the block bootstrap standard errors (m=1,000), which accounts for the estimation error arising from the marginal distribution. See Patton (2013) for detailed description. ** and * denote significance at the 1% and 5% level, respectively.

Table 1.6 – Student's t Copula Implied Kendall's τ Rank Coefficients and Tail Dependence Coefficients

	Rank & Tail Coefficients	2013	2014	2015	2016	2017	2018
Bank of China	Kendall's τ	0.3029	0.3024	0.3316	0.4313	0.5742	0.5327
	Tail	0.2563	0.2576	0.2789	0.3663	0.4961	0.4539
Development Bank	Kendall's τ	0.2613	0.2525	0.2607	0.2788	0.3475	0.3771
	Tail	0.0443	0.0418	0.0457	0.0516	0.0802	0.0934
Export-Import Bank	Kendall's τ	0.2918	0.2770	0.2810	0.2657	0.2862	0.3008
	Tail	0.0585	0.0527	0.0545	0.0495	0.0561	0.0614
ICBC	Kendall's τ	-	-	-	-	0.5398	0.4698
	Tail	-	-	-	-	0.5538	0.4884

This table shows the implied Kendall's τ rank correlation coefficient and tail dependence coefficient for the selected copula formulation of each sovereign-bank CDS pair. Each sovereign-bank CDS pair is represented using the bank's name. Data are expressed in average value and reported on a yearly basis.

selected copula model at the 5% significant level for all pairs. Table 1.5 reports the parameter estimates of the selected copula models. The correlation parameter ρ of static Student's t copula suggests a significant positive dependence for all sovereign-bank CDS pairs. The significant estimates α and β in the dynamic GAS copula formulation confirm the dependence structure is time-varying. In terms of the estimates for dynamic ARMA copula formulation, the significant estimate ψ and φ of Chexim suggests the time-varying dependence structure is controlled by both γ_t and Γ_t.

Table 1.6 reports the tail dependence coefficients and Kendall's τ rank correlation coefficients implied by the selected copula models. The daily tail dependence coefficients and rank correlation coefficients are averaged and reported on a yearly basis. The reported tail dependence coefficients are the same for both upper and lower tails since the selected copula models are Student's t copula for all sovereign-bank CDS pairs. Figure 1.3 plots the daily dynamics of implied time-varying tail dependence coefficients of the selected copula formulation. The dynamic tail dependence coefficients are plotted together with the corresponding static tail dependence coefficient. The time series for all pairs cover the period from January 01, 2013 to November 23, 2018 except for the China sovereign CDS and ICBC CDS pair, which is from September 15, 2017 to November 23, 2018.

We can draw following conclusions from the results shown in Table1.6 and Figure

1.3: First, China sovereign CDS returns have a higher tail dependence coefficient with commercial bank CDS returns than with policy bank CDS returns. Table 1.6 shows the average tail dependence coefficient for the sovereign and commercial bank CDS pair is 0.393, while the average tail dependence coefficient for the sovereign and policy bank CDS pair is 0.057. This holds for Kendall's τ rank correlation coefficient as well. For example, the average rank correlation coefficient between China sovereign CDS returns and commercial bank CDS returns is 0.413, while the average rank correlation coefficient between China sovereign CDS returns and policy bank CDS returns is 0.290.

The second conclusion is that the likelihood of joint extreme movements of sovereign CDS returns and bank CDS returns has increased in recent years. Figure 1.3 shows a clear increase in tail dependence coefficient for the China sovereign CDS and BoC CDS pair, as well as the China sovereign CDS and CDB CDS pair. This is consistent with the behavior of rank correlation coefficients shown in Figure 1.2. Although we cannot observe a clear change of regime for the China sovereign CDS and Chexim CDS pair, the dependence coefficient is stabilized at a slightly higher level after 2017. To be precise, the tail dependence coefficient is within the range [0.0424, 0.0788] after January 2017. It is much more stable than the tail dependence coefficient from the 2013 to 2016 period. The tail dependence coefficient from 2013 to 2016 was within range [0.0301, 0.0987]. Table 1.1 provides the potential reason for the increased tail dependence. China sovereign CDS became the largest net insured single-name sovereign CDS contract in 2017. This increasing interest in China sovereign CDS contracts gives investors a stronger incentive to monitor its relationship with the domestic bank industry. Unfortunately, ICBC CDS data are only avaliable from September 15, 2017 to November 23, 2018, which does not allow us to investigate the change of tail dependence.

1.6.3 Time Series Regression

Table 1.7 shows the estimation results of the daily time series regression of China sovereign CDS spread changes on local and global variables for all four sub-periods. U.S. stock market returns and changes in the high-yield spreads are the most important global explanatory variables. This is consistent with the findings in Longstaff et

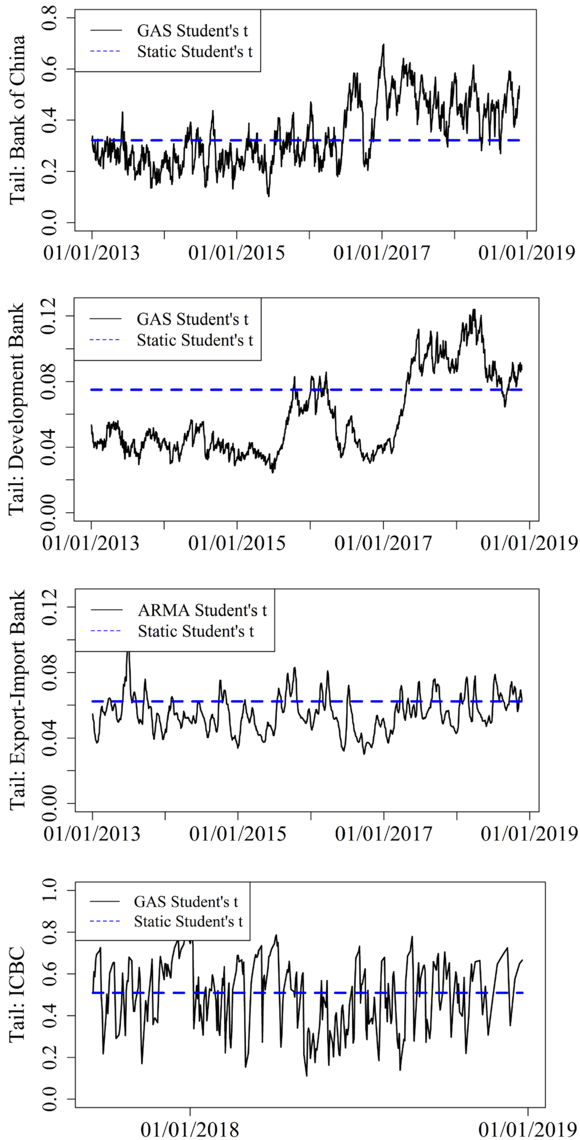


Figure 1.3 – Implied Tail Dependence Coefficients of Sovereign-Bank CDS pairs: Best Selected Dynamic Copula versus Static Copula

al. (2011). The negative relationship between U.S. stock market returns and China sovereign CDS spread changes suggests that a distressed global economic condition, measured by the decline in U.S. stock market prices, is associated with an increase in China sovereign CDS spreads. The positive relationship between the high-yield spread and China sovereign CDS spreads suggests an increase in U.S. corporate high-yield spread is associated with an increase in China sovereign CDS spreads. We use the estimation results of the post-stock market turbulence period for economic interpretation. Table 1.7 Panel C column (1) shows the estimated coefficient on U.S. stock market returns is -1.469. This implies a 10% increase in the U.S. stock market prices is associated with around a 14.7% decrease in China sovereign CDS spreads. Similarly, the estimated coefficient on the high-yield spread changes is 0.159. This suggests a 10% increase in high-yield spread is associated with around 1.6% increase in China sovereign CDS spreads.

The estimated coefficients on local stock market returns are statistically significant at the 5% level for all sub-periods. The negative sign is as expected and suggests that a decline in local stock market prices is associated with an increase in China sovereign CDS spreads. The offshore exchange rate and implied volatility became two important local factors during the post-stock market turbulence period and the U.S.-China trade war period. The coefficients on both factors are statistically significant at the 5% level. The positive relationship between exchange rate and sovereign CDS spread suggests a depreciation in local currency is associated with an increase in China sovereign CDS spreads. The positive relationship between implied volatility and credit spread suggests that an increase in stock market volatility is associated with an increase in China sovereign CDS spreads. The transparency in the currency exchange market has largely been improved since 2016. In that same year, the Chinese Yuan joined the U.S. dollar, Euro, Japanese Yen and British Pound in the SDR basket. This explains its statistically significant coefficient during the post-stock market turbulence and U.S.-China trade war periods. We use the estimation results of the post-stock market turbulence period for economic interpretation. Table 1.7 Panel C column (4) shows the estimated coefficient on exchange rate changes is 1.373. This implies an 10% increase in the offshore exchange rate is associated with around 13.7% decrease in China sovereign CDS spreads. We notice the change in offshore exchange rate and the orthogonalized change in implied volatility have

Table 1.7 – Daily Regression of China Sovereign CDS Spread Changes on Local and Global Variables

Panel A: Pre-Stock Market Turbulence Period (January 01, 2013 to September 05, 2014)									
ΔLog(CDS)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
U.S. Stock Return	−2.325**	−2.074**	−2.249**	−2.262**	−2.324**	−2.319**	−2.342**		−2.046**
	(0.396)	(0.364)	(0.363)	(0.418)	(0.397)	(0.401)	(0.406)		(0.373)
ΔInvestment	0.020	0.025	0.010	0.024	0.020	0.021	0.009		0.010
	(0.069)	(0.064)	(0.057)	(0.069)	(0.071)	(0.070)	(0.063)		(0.054)
ΔHigh	0.263*	0.187	0.252*	0.273*	0.263*	0.267*	0.260*		0.192
	(0.110)	(0.098)	(0.105)	(0.112)	(0.110)	(0.109)	(0.110)		(0.098)
Local Stock Return		−1.040**						−1.279**	−0.972**
		(0.196)						(0.219)	(0.199)
ΔImplied Volatility			0.139					0.106	0.064
			(0.092)					(0.115)	(0.087)
ΔFX				1.548				2.094	0.524
				(1.630)				(1.542)	(1.587)
ΔGovt10yr					0.193			0.004	−0.185
					(3.358)			(3.535)	(3.338)
ΔSlope						0.002		0.001	0.002
						(0.005)		(0.006)	(0.005)
Bank Stock Return							−0.283	−0.290	−0.287
							(0.377)	(0.395)	(0.355)
Intercept	0.003	0.002	0.003	0.003	0.003	0.003	0.003	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Obs	350	350	350	350	350	350	350	350	350
R^2	0.246	0.321	0.261	0.248	0.246	0.247	0.248	0.162	0.326
Panel B: Stock Market Turbulence Period (September 08, 2014 to February 11, 2016)									
ΔLog(CDS)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
U.S. Stock Return	−1.376**	−1.214**	−1.382**	−1.373**	−1.383**	−1.376**	−1.376**		−1.217**
	(0.170)	(0.159)	(0.168)	(0.170)	(0.169)	(0.170)	(0.170)		(0.159)
ΔInvestment	0.467**	0.435**	0.465**	0.467**	0.460**	0.467**	0.467**		0.429**
	(0.120)	(0.118)	(0.122)	(0.120)	(0.114)	(0.120)	(0.120)		(0.115)
ΔHigh	0.218**	0.191**	0.210**	0.217**	0.224**	0.218**	0.219**		0.197**
	(0.052)	(0.047)	(0.052)	(0.053)	(0.051)	(0.052)	(0.052)		(0.047)
Local Stock Return		−0.472**						−0.938**	−0.462**
		(0.100)						(0.114)	(0.097)
ΔImplied Volatility			0.042					−0.006	0.006
			(0.030)					(0.040)	(0.026)
ΔFX				0.219				1.035	0.379
				(0.472)				(0.533)	(0.450)
ΔGovt10yr					−7.111			−4.398	−9.919
					(5.686)			(7.534)	(6.360)
ΔSlope						−0.000		0.018	0.023
						(0.017)		(0.025)	(0.020)
Bank Stock Return							−0.055	0.033	−0.061
							(0.193)	(0.252)	(0.178)
Intercept	0.000	−0.000	0.000	0.000	−0.000	0.000	0.000	0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Obs	303	303	303	303	303	303	303	303	303
R^2	0.430	0.469	0.435	0.431	0.434	0.430	0.430	0.182	0.476

no explanatory power for China sovereign CDS spread changes before 2016. The potential reasons for the statistically insignificant coefficients on those factors are that, first, investors started to pay more attention to the domestic economic indicators when the China sovereign CDS contract became one of the top two net insured single-name sovereign CDS contracts. This could potentially explain why the coefficient on implied volatility has become statically significant since 2016. Second, as stressed above, the transparency in the currency exchange market has largely been improved since the Chinese Yuan was included in the SDR basket in 2016.

Continue

Panel C: Post-Stock Market Turbulence Period (February 12, 2016 to January 05, 2018)									
ΔLog(CDS)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
U.S. Stock Return	−1.469** (0.168)	−1.312** (0.173)	−1.459** (0.170)	−1.426** (0.173)	−1.474** (0.167)	−1.477** (0.166)	−1.522** (0.175)		−1.382** (0.185)
ΔInvestment	0.005 (0.039)	0.001 (0.038)	0.005 (0.038)	0.006 (0.039)	0.007 (0.040)	0.006 (0.039)	0.004 (0.039)		0.004 (0.038)
ΔHigh	0.159** (0.047)	0.150** (0.045)	0.156** (0.046)	0.170** (0.052)	0.159** (0.047)	0.158** (0.047)	0.152** (0.047)		0.152** (0.048)
Local Stock Return		−0.343** (0.115)						−0.679** (0.141)	−0.246* (0.123)
ΔImplied Volatility			0.074* (0.032)					0.050 (0.042)	0.065 (0.035)
ΔFX				1.373** (0.430)				1.320** (0.473)	1.444** (0.416)
ΔGovt10yr					3.911 (4.397)			2.061 (4.501)	4.434 (4.125)
ΔSlope						0.001 (0.002)		0.001 (0.002)	0.002 (0.002)
Bank Stock Return							−0.224 (0.155)	−0.145 (0.168)	−0.269 (0.160)
Intercept	−0.001 (0.001)	−0.001 (0.001)	−0.001 (0.001)	−0.001 (0.001)	−0.001 (0.001)	−0.001 (0.001)	−0.001 (0.001)	−0.002 (0.001)	−0.001 (0.001)
Obs	410	410	410	410	410	410	410	410	410
R^2	0.218	0.232	0.229	0.236	0.219	0.219	0.223	0.098	0.267

Panel D: U.S-China Trade War Period (January 08, 2018 to November 23, 2018)									
ΔLog(CDS)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
U.S. Stock Return	−0.535* (0.268)	−0.247 (0.274)	−0.416 (0.258)	−0.362 (0.273)	−0.527 (0.269)	−0.522 (0.268)	−0.669* (0.267)		−0.230 (0.278)
ΔInvestment	0.035 (0.100)	0.084 (0.097)	−0.007 (0.105)	0.058 (0.100)	0.030 (0.102)	0.032 (0.100)	0.021 (0.101)		0.040 (0.105)
ΔHigh	0.469** (0.110)	0.425** (0.103)	0.467** (0.112)	0.481** (0.112)	0.466** (0.111)	0.464** (0.109)	0.453** (0.107)		0.423** (0.105)
Local Stock Return		−0.597** (0.152)						−0.784** (0.145)	−0.458** (0.165)
ΔImplied Volatility			0.151** (0.042)					0.095* (0.043)	0.097* (0.041)
ΔFX				1.430* (0.603)				0.946 (0.691)	0.737 (0.549)
ΔGovt10yr					−12.141 (8.853)			−4.485 (8.831)	−5.381 (8.927)
ΔSlope						−0.028 (0.022)		−0.039 (0.020)	−0.029 (0.020)
Bank Stock Return							−0.378 (0.217)	−0.126 (0.234)	−0.279 (0.238)
Intercept	0.001 (0.002)	0.001 (0.002)	0.002 (0.002)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)	0.001 (0.001)	0.001 (0.002)
Obs	184	184	184	184	184	184	184	184	184
R^2	0.252	0.308	0.297	0.280	0.259	0.260	0.267	0.231	0.360

This table reports the estimation results of the daily time series regression specified in eq(1.11) for all four sub-periods. U.S. stock returns are the daily excess return of MSCI USA index. ΔInvestment is the daily percentage changes in the yield spread between S&P 500 BBB corporate bond yield and S&P 500 AAA corporate bond yield. ΔHigh is the daily percentage changes in the yield spread between S&P 500 BB corporate bond yield and S&P 500 BBB corporate bond yield. Local stock returns are the orthogonalized daily percentage changes in MSCI China index. ΔImplied Volatility is the orthogonalized daily percentage changes in VXFXI, which is the CBOE China ETF Volatility Index. ΔFX is the daily percentage changes in offshore exchange rates, which is expressed as units of Chinese Yuan per U.S. dollar. ΔGovt10yr is the daily percentage changes in China ten-year government bond yields. ΔSlope is the daily percentage changes in the yield spread between China ten-year and two-year government bond yields. Bank stock returns are the orthogonalized daily percentage changes in the self-constructed China bank index, which includes Hong Kong listed banks headquartered in mainland China. Robust standard errors are reported in parentheses.

** Denotes significance at the 1% level.

* Denotes significance at the 5% level.

Table 1.8 – Monthly Regression of China Sovereign CDS Spread Changes with Macroeconomic and Investment-Flow Variables

ΔLog(CDS)	(1)	(2)	(3)
U.S. Stock Return	−0.789 (0.506)		−0.573 (0.662)
ΔInvestment	0.120 (0.162)		0.092 (0.196)
ΔHigh	0.067 (0.079)		0.037 (0.086)
Local Stock Return	−0.968** (0.291)		−1.046** (0.324)
ΔImplied Volatility	0.283** (0.106)		0.278* (0.113)
ΔFX	−0.708 (1.124)		−0.543 (1.417)
ΔGovt10yr	0.003 (0.336)		−0.084 (0.426)
ΔSlope	0.005 (0.023)		0.006 (0.029)
Bank Stock Return	−0.291 (0.376)		−0.210 (0.482)
ΔDebt/GDP		6.129 (7.347)	2.884 (7.414)
ΔReal Rate		1.721 (4.236)	3.048 (3.977)
ΔReserve/GDP		−11.574** (4..228)	−3.569 (3.969)
ΔUncertainty		0.194 (0.122)	0.024 (0.128)
ΔBudget/GDP		0.390 (1.485)	−0.477 (1.335)
ΔToT Volatility		−1.546 (7.946)	0.627 (5.973)
Equity Net Flow		0.014 (0.009)	0.001 (0.009)
Bond Net Flow		−0.003 (0.004)	0.001 (0.004)
Intercept	0.011 (0.012)	−0.011 (0.021)	0.000 (0.018)
Obs	67	64	64
R^2	0.429	0.151	0.450

This table reports the estimation results of the monthly time series regression specified in eq(1.12). The macroeconomic and investment-flow variables include the monthly change in the China external debt over GDP ratio, China real interest rate, China foreign currency reserve over GDP ratio, China economic policy uncertainty Index, China government budget balance over GDP ratio, 18-month rolling volatility of China terms of trades, and equity and bond net flow. The China State Administration of Foreign Exchange changed the definition of external debt in 2015, producing an outlier for the external debt/GDP ratio in 2015Q1. We delete three months of data caused by this change of definition to reduce the power of outliers. This yields 64 observations shown in columns (2) and (3). The local and global variables are the same variables defined in eq(1.11) but in monthly frequency. Robust standard errors are reported in parentheses.
** Denotes significance at the 1% level.
* Denotes significance at the 5% level.

Local factors become more relevant in explaining the China sovereign CDS spread changes during the U.S.-China trade war period. A direct comparison of the R^2s shown in Table 1.7 Panel D column (1) and (8) shows that the combined explanatory power of local factors (R^2=23.1%) is comparable to the combined explanatory power of global factors (R^2=25.2%). It is also higher than the R^2s for all the pre-, during, and post-stock market turbulence periods shown in Table 1.7 Panel A, B, C column (8). The increased R^2 of local factors during the U.S.–China trade war period indicates investors believe trade war will have a direct impact on the Chinese local economy and they thus pay more attention to the domestic fundamentals during this period. Our results are quite robust for the following reasons: first, our local stock market returns and implied volatility changes are the orthogonalized series and, therefore, their explanatory powers are unaffected by the global variables. Second, the mean VIF value for each regression in every sub-period is below 1.33. This indicates our regression analysis does not suffer from the multicollinearity problem. For each series, we also perform Durbin-Watson test on the regression residuals. The d-statistics are all close to 2, and we accept no serial correlation at the 95% confidence level.

The foreign currency reserve/GDP ratio is the only important macroeconomic variable for China sovereign CDS spread changes as shown in Table 1.8. However, its explanatory power for the sovereign CDS spread disappeared after we control for the other local and global determinants. The negative sign is as expected and suggests that a decline in foreign currency reserve/GDP ratio is associated with an increase in China sovereign CDS spreads. We use the estimation result of the percentage changes of foreign currency reserve/GDP ratio for economic interpretation.[27] A 10% increase in foreign currency reserve/GDP ratio is associated with a 34% decrease in the sovereign CDS spreads. Strikingly, none of the other monthly macroeconomic variables are important. This implies macroeconomic variables might be more meaningful in explaining the sovereign CDS spread levels rather than changes. R^2 only

[27]We use the monthly changes rather than percentage changes of the additional control variables in monthly regression analysis because the monthly real rates remain at zero for several months. This characteristic does not allow us to use percentage changes for calculation. Therefore, we use the simple monthly changes for all additional monthly explanatory variables for the sake of consistency. For the purpose of economic interpretation of foreign currency reserve/GDP, we use the coefficient on the percentage changes of this variable, which is obtained by re-estimating the regression using the percentage changes of foreign currency reserve/GDP.

increases slightly from 0.429 to 0.450 after adding the additional eight monthly investment-flow and macroeconomic variables.

1.7 Conclusion

This paper first examines the relationship between China sovereign CDS spreads and bank CDS spreads, and second studies the determinants of daily and monthly China sovereign CDS spread changes. We address the following two questions for the relationship between sovereign and bank CDS: first, are China sovereign CDS spreads more likely to get extreme joint upward movement with commercial bank CDS spreads or policy bank CDS spreads? Second, does the China sovereign and bank CDS relationship get strengthened over the years? We further address the following three questions for the determinants of China sovereign CDS spread changes: first, what are the important local and global factors in explaining the daily China sovereign CDS spread changes? Second, do local factors become more important for China sovereign CDS spreads during a crisis period, such as the U.S.−China trade war period? Third, what are the important macroeconomic or investment-flow variables that can explain the monthly China sovereign CDS spread changes?

We use two approaches to answer these questions: the copula model and regression analysis. The copula model is used to study the joint extreme movements of China sovereign and bank CDS spreads. It allows us to study the probability of simultaneous large increases in both sovereign and bank credit risks. Time series regression is used to study the determinants of China sovereign CDS spread changes. We perform regression analyses in both daily and monthly frequencies. For the daily time series regression, we include commonly used local and global variables, as well as implied volatility as an additional local factor. Macroeconomic variables are only included in the monthly time series regression. This choice is based on the empirical findings in Eyssell et al. (2013). For instance, their paper use Debt-over-GDP as one of the determinants to study the daily China sovereign CDS spread changes and find the coefficient is negatively significant at the 1% significance level. Therefore, we do not use linear or spline interpolation to obtain the macroeconomic variables in daily frequency.

Our results from the copula model show the tail dependence coefficient is higher for the sovereign−commercial bank CDS pair than for the sovereign−policy bank CDS pair. The dynamic structure of the tail dependence coefficient shows an increase in the tail dependence coefficient for the BoC and sovereign CDS pair, as well as the CDB and sovereign CDS pair. This strengthened tail dependence suggests a higher likelihood of joint extreme movements. Our regression results show that the most important global factors for daily China sovereign CDS spread changes are the U.S. stock market returns and the percentage changes in U.S. high-yield spreads. Local factors become more relevant in explaining the China sovereign CDS spread changes during the U.S.−China trade war period and the post-stock market turbulence period. The foreign currency reserve/GDP ratio is the only important macroeconomic variable in explaining the monthly China sovereign CDS spread changes.

Our paper is relevant for academics, investors, and policymakers. For academics, we show that the change in offshore exchange rate and implied volatility are two important factors in explaining the China sovereign CDS spread changes. Both factors are not included in Eyssell et al. (2013) but should be included as domestic factors in future study. We also show a strong relationship between the China sovereign and bank CDS spreads by providing the first study on the tail dependence analysis. The dynamic relationship between sovereign and bank credit risk could be studied further in the future. For investors, our results on strengthened tail dependence coefficient of bank-sovereign CDS pair suggests that investors should closely watch the condition of the China domestic banking system when monitoring China sovereign credit risk. Moreover, our regression results suggest domestic factors play an equally important role as global factors in assessing the China sovereign credit risk during a crisis period. For policymakers, our results call for a closer monitoring and risk assessment in domestic banking sector, stock exchange, and currency exchange markets. With the opening of the Chinese domestic financial market, we hope to see more commercial bank CDSs are available for investigation in addition to the big state-owned banks and policy banks. Moreover, we expect more local industries, such as energy and insurance, will be CDS referenced. This will allow us to have a deep understanding of the structure of the Chinese economy and its influence on the China sovereign credit risk.

Bibliography

Acharya, V., Drechsler, I., Schnabl, P., 2014. A pyrrhic victory? Bank bailouts and sovereign credit risk. *Journal of Finance* 69 (6), 2689-2739.

Atil, A., Bradford, M., Elmarzougui, A., Lahiani, A., 2016. Conditional dependence of US and EU sovereign CDS: A time-varying copula-based estimation. *Finance Research Letters* 19, 42-53.

Augustin, P., Sokolovski, V., Subrahmanyam, M.G., Tomio, D., 2016. Why do investors buy sovereign default insurance? *CFS Working Paper 540*, Center for Financial Studies.

Augustin, P., 2018. The term structure of CDS spreads and sovereign credit risk. *Journal of Monetary Economics* 96, 53-76.

Avino, D., Cotter, J., 2014. Sovereign and bank CDS spreads: Two sides of the same coins. *Journal of International Financial Markets, Institutions & Money* 32, 72-85.

Bai, J., Perron, P., 2003. Computation and analysis of multiple structural change models. *Journal of Applied Econometrics* 18 (1), 1-22.

Baker, R.S., Bloom, N., Davis, J.S., 2016. Measuring economic policy uncertainty. *Quarterly Journal of Economics* 131 (4), 1593-1636.

Blommestein, H., Eijffinger, S., Qian, Z.X., 2016. Regime-dependent determinants of Euro area sovereign CDS spreads. *Journal of Financial Stability* 22, 10-21.

Bollerslev, T., Gibson, M., Zhou, H., 2011. Dynamic estimation of volatility risk premia and investor risk aversion from option-implied and realized volatilities. *Journal of Econometrics* 160 (1), 235-245.

Cao, C., Yu, F., Zhong, Z., 2010. The information content of option-implied volatility for credit default swap valuation. *Journal of Financial Markets* 13 (3), 321-343.

Christiansen, C., Ranaldo, A., Söderlind, P., 2011. The time-varying systematic risk of carry trade strategies. *Journal of Financial and Quantitative Analysis* 46 (4), 1107-1125.

Chollete, C., Peña, V.D.L., Lu, C.C., 2011. International diversification: A copula approach. *Journal of Banking & Finance* 35 (2), 403-417.

Cochrane, J. H., Piazzesi, M., 2005. Bond risk premia. *American Economic Review* 95 (1), 138-160.

Collin-Dufresne, P., Goldstein, S.R., Martin, J.S., 2001. The determinants of credit spread changes. *Journal of Finance* 56 (6), 2177-2207.

Cooper, R., Nikolov, K., 2018. Government debt and banking fragility: The spreading of strategic uncertainty. *International Economic Review* 59 (4), 1905-1925.

Cremers, M., Driessen, J., Maenhout, P., Weinbaum, D., 2008. Individual stock-option prices and credit spreads. *Journal of Banking & Finance* 32 (12), 2706-2715.

Creal, D., Koopman S.J., Lucas, A., 2013. Generalized autoregressive score models with applications. *Journal of Applied Econometrics* 28 (5), 777-795.

Das, S., 2019. China's evolving exchange rate regime. *IMF Working Paper No.19/50*.

Diebold, F.X., Gunther, T.A., Tay, A.S., 1998. Evaluating density forecasts with applications to financial risk management. *International Economic Review* 39 (4), 863-883.

Dieckmann, S., Plank, T., 2012. Default risk of advanced economies: An empirical analysis of credit default swaps during the financial crisis. *Review of Finance* 16 (4), 903-934.

Engle, R., 1982. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica* 50 (4), 987-1007.

Eyssell, T., Fung, H.G., Zhang, G., 2013. Determinants and price discovery of China sovereign credit default swaps. *China Economic Review* 24, 1-15.

Farhi, E., Tirole, J., 2018. Deadly embrace: Sovereign and financial balance sheets doom loops. *Review of Economic Studies* 85 (3), 1781-1823.

Fei, F., Fuertes, A.M., Kalotychou, E., 2017. Dependence in credit default swap and equity markets: Dynamic copula with Markov-switching. *International Journal of Forecasting* 33 (3), 662-678.

Fontana, A., Scheicher, M., 2016. An analysis of euro area sovereign CDS and their relation with government bonds. *Journal of Banking & Finance* 62, 126-140.

Garman, B.M., Klass, J.M., 1980. On the estimation of security price volatilities from historical data. *Journal of Business* 53 (1), 67-78.

Hansen, B.E., 1994. Autoregressive conditional density estimation. *International Economic Review* 35 (3), 705-730.

Hilscher, J., Nosbusch, Y., 2010. Determinants of sovereign risk: Macroeconomic fundamentals and the pricing of sovereign risk. *Review of Finance* 14 (2), 235-262.

Joe, H., 2005. Asymptotic efficiency of the two-stage estimation method for copula-based models. *Journal of Multivariate Analysis* 94 (2), 401-419.

Kallestrup, R., Lando, D., Murgocic, A., 2016. Financial sector linkages and the dynamics of bank and sovereign credit spreads. *Journal of Empirical Finance* 38, 374-393.

Kilic, E., 2017. Contagion effects of U.S. Dollar and Chinese Yuan in forward and spot foreign exchange markets. *Economic Modelling* 62, 51-67.

Liu, D., 2009. Banking and financial sector reforms in China: Experience and prospects for the futures. 1st ed. *Resurgent China: Issues for the Future*, 258-288, London: Palgrave Macmillan.

Longstaff, F.A., Pan, J., Pedersen, L.H., Singleton, K.J., 2011. How sovereign is sovereign credit risk? *American Economic Journal: Macroeconomics* 3 (2), 75-103.

Longstaff, F. A., Schwatrz, E. S., 1995. A simple approach to valuing risky fixed and floating rate debt. *Journal of Finance* 50 (3), 789-819.

Meine, C., Supper, H., Weiß, G., 2016. Is tail risk priced in credit default swap premia? *Review of Finance* 20 (1), 287-336.

Oehmke, M., Zawadowski, A., 2017. The anatomy of the CDS market. *Review of Financial Studies* 30 (1), 80-119.

Pan, J., Singleton, K.J., 2008. Default and recovery implicit in the term structure of sovereign CDS spreads. *The Journal of Finance* 63 (5), 2345-2384.

Patton, A.J., 2006. Modelling asymmetric exchange rate dependence. *International Economic Review* 47 (2), 527-556.

Patton, A.J., Politis, D., White, H., 2009. Correction to "Automatic block-length selection for the dependent bootstrap." *Econometric Reviews* 28 (4), 372-375.

Patton, A.J., 2013. Copula methods for forecasting multivariate time series. *Handbook of Economic Forecasting* 2, 899-960.

Reboredo, J.,C., 2011. How do crude oil prices co-move? A copula approach. *Energy Economics* 33 (5), 948-955.

Singh, M., Nejadmalayeri, A., Lucey, B., 2013. Do U.S. macroeconomic surprises influence equity returns? An exploratory analysis of developed economies. *Quarterly Review of Economics and Finance* 53 (4), 476-485.

Sornette, D., Demos, G., Zhang, Q., Cauwels, P., Filimonov, V., Zhang, Q.Z., 2015. Real-time prediction and post-mortem analysis of the Shanghai 2015 stock market bubble and crash. *Swiss Finance Institute Research Paper No. 15-31* .

Wang, K., Chen, Y.H., Huang, S.W., 2011. The dynamic dependence between the Chinese market and other international stock markets: A time-varying copula approach. *International Review of Economics & Finance* 20 (4), 654-664.

Appendix

Data: Definition and Source

1. **China Sovereign Credit Default Swap (CDS) Spreads.** The five-year China sovereign CDS bid and ask quotes are obtained from Credit Market Analysis (CMA), which provides the end-of-day full curves for single-name sovereign CDS contracts at 5 p.m. New York time. The daily mid-quote of sovereign CDS is calculated as the average value of daily bid and ask. Following Longstaff et al. (2011), the monthly CDS quotes are constructed as the mid-quotes on the last trading day of the month.

2. **China Sovereign CDS Net Notional Amount Outstanding.** The net notional amount outstanding is the sum of the net protection bought by net buyers (or net protection sold by net sellers). It is denominated in million U.S. dollars and collected from the Depository Trust & Clearing Corporation (DTCC).

3. **External Debt.** The external debt is the debt securities owed by Chinese residents to non-residents. It is denominated in million U.S. dollars and collected from the State Administration of Foreign Exchange.[28] We use linear interpolation to transform the quarterly data into monthly frequency.

4. **Foreign Currency Reserve.** The monthly foreign currency holding denominated in trillion U.S. dollars is collected from the State Administration of Foreign Exchange.

5. **China Economic Policy Uncertainty Index.** The China economic policy uncertainty index is constructed using Baker et al.'s (2016) method. It is a news-based index. Higher index value indicate higher economic uncertainty. Data are directly obtained from economic policy uncertainty website.[29]

[28] The State Administration of Foreign Exchange defined the external debt as the foreign currency denominated debt securities before 2015Q1. After 2015Q1, the external debt was defined as the total debt securities debt including both foreign currency denominated and domestic currency denominated debt securities. We acknowledge this change of definition and delete three months data in our monthly regression analysis caused by this change of definition.

[29] The economic policy uncertainty website: https://www.policyuncertainty.com/.

6. **Terms of Trade Volatility.** The 18-month rolling volatility of terms of trades (Dieckmann and Plank, 2012; Hilscher and Nosbusch, 2010).

7. **Bond and Equity Flows.** Bond and equity flows are the monthly net new flows (inflows minus outflows) to long-term bond and equity mutual funds, respectively. Monthly data are obtained from the Investment Company Institute.

8. **Local Stock Market Returns.** Local stock market return comprises the daily returns of Morgan Stanley Capital International (MSCI) China index. Following Blommestein et al. (2016) and Fontana and Scheicher (2016), we use the orthogonalized local stock market returns to improve identification. Asian markets are highly affected by the overnight movements of the U.S. stock market. Therefore, we orthogonalized the local stock market returns by the lagged U.S. stock market returns to remove the influence of the U.S. stock market.

9. **Implied Volatility.** We use the CBOE China ETF volatility Index (VXFXI) as the implied volatility proxy. VXFXI applies VIX methodology to measure the market's expectation of the implied volatility of the U.S. traded iShares China Large-Cap ETF. The VXFXI is highly correlated with VIX, since it is calculated based on the ETF traded in the United States. To improve identification, we construct the orthogonalized percentage changes in VXFXI as the sum of intercept and residuals from a regression of percentage changes in VXFXI on the percentage changes in VIX.

10. **Exchange Rate.** The exchange rate is expressed as units of local currency per U.S. dollar. We use the offshore exchange rate based on executable quotes. Data are collected from Bloomberg using source Bloomberg generic price executable (BNGE). The end-of-day BNGE bid and ask quotes are the executable bid and ask quotes at 5 p.m. New York time. The daily mid-quote of the exchange rate is calculated as the average value of daily bid and ask.

11. **Government Bond Yield.** The government bond yield is the ten-year China government bond yield collected from Datastream. It is the proxy for spot rate.

12. **Slope of Yield Curve.** The slope of yield curve is the difference between ten-year and two-year China government bond yields.

13. **Corporate Yield Spreads.**[30] The investment-grade yield spreads are the spreads between the Standard & Poor's (S&P) 500 BBB corporate bond index and the S&P 500 AAA corporate bond index. High-yield spreads are the spreads between the S&P 500 BB corporate bond index and the S&P 500 BBB corporate bond index. Data are collected from S&P.

14. **Fiscal Balance.** The fiscal balance is the Chinese government budget balance as a percentage of GDP. The fiscal balance measures the difference between a government's revenues and expenditures. Data are collected from Datastream.

15. **Real Interest Rate.** China's real interest rate is calculated as the difference between the monthly one-year nominal deposit rate and the inflation rate, following Eyssell et al. (2013). Monthly deposit rates and inflation rates are collected from Bloomberg and the World Bank.

16. **China Bank CDS Spreads.** The five-year bank CDS bid and ask quotes are obtained from CMA. The daily mid-quote is calculated as the average value of bid and ask. The time series for the Bank of China CDS, China Development Bank CDS, and the Export-Import Bank of China CDS covers the period from January 01, 2013 to November 23, 2018. The CDS spreads of Industrial and Commercial Bank of China are from September 15, 2017 to November 23, 2018.

17. **U.S. Stock Market Returns.** The U.S. stock market returns[31] are the daily excess returns of the MSCI USA index, which is calculated as the daily MSCI USA index returns minus the daily Treasury-bill returns, similar to the Fama-French factor. The MSCI USA index data are obtained from Bloomberg. The daily Treasury-bill returns are collected directly form the Ken French website.[32]

[30] The alternative proxies for corporate yield spreads can be computed using Intercontinental Exchange (ICE) Bank of America Merrill Lynch (BofAML) U.S. Corporate AAA, BBB, and BB effective yields from the Federal Reserve Bank of St. Louis. The estimation results are similar to ours.

[31] One can directly use the U.S. stock market returns provided by Ken French. It is calculated as the excess return on all NYSE, AMEX, and NASDAQ stocks (from CRSP) minus the one-month Treasury-bill return (from Ibbotson Associates). It yields similar estimation results as ours.

[32] Ken French website: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

18. **China Bank Stock Returns.** The China bank stock returns are the daily returns of the self-constructed China bank index, which includes Hong Kong listed banks headquartered in mainland China. To be precise, we include the following banks: the Industrial and Commercial Bank of China, the China Construction Bank, the Agricultural Bank of China, the Bank of China, China Merchants Bank, the Bank of Communications, China Citic Bank, ChongQing Rural Commercial Bank, and China MinSheng Bank. The China bank index is constructed as the market capitalisation weighted index. China bank stock returns are affected by the domestic stock market returns as well as the overnight U.S. bank stock returns. To improve identification, we orthogonalized the China bank stock returns by the lagged U.S. bank stock returns and the orthogonalized local stock market returns. The U.S. bank index is the Dow Jones U.S. bank index collected from S&P.

Copula Formulations

1. **Gaussian Copula (Elliptical)** The bivariate Gaussian copula cdf is defined as:

$$C(u_1,u_2;\rho) = \int_{-\infty}^{\Phi^{-1}(u_1)} \int_{-\infty}^{\Phi^{-1}(u_2)} \frac{1}{2\pi\sqrt{1-\rho^2}} \exp(\frac{2\rho rs - r^2 - s^2}{2(1-\rho^2)}) drds$$

where Φ^{-1} is the inverse of univariate standardized Gaussian cumulative distribution function and ρ is the Pearson's correlation coefficient. The coefficients of lower and upper tail dependence for the Gaussian copula are $\lambda^U = \lambda^L = 0$. The implied Kendall's τ is $\frac{2}{\pi} arcsin(\rho)$.

2. **Student's t Copula (Elliptical)** The bivariate Student's t copula cdf is defined as:

$$C(u_1,u_2;\rho,v) = \int_{-\infty}^{t_v^{-1}(u_1)} \int_{-\infty}^{t_v^{-1}(u_2)} \frac{1}{2\pi\sqrt{1-\rho^2}} (1+\frac{r^2+s^2-2\rho rs}{v(1-\rho^2)})^{-\frac{v+2}{2}} drds$$

where t_v^{-1} is the inverse of Student's t cumulative distribution function with $v > 2$ degrees of freedom. Student's t copula captures symmetric upper and lower tail dependencies. λ^U=λ^L=$2 * t_{v+1}(-\sqrt{v+1}\sqrt{\frac{1-\rho}{1+\rho}})$, where t_{v+1} denotes the cdf of a univariate Student's t distribution with $v+1$ degrees of freedom. A stronger linear correlation ρ and a lower degree of freedom v lead to a stronger tail dependence. The implied Kendall's τ is $\frac{2}{\pi} arcsin(\rho)$.

3. **Gumbel Copula (Archimedean)** The bivariate Gumbel cdf is defined as:

$$C(u_1,u_2;\delta) = \exp\{-[(-\log u_1)^{\delta} + (-\log u_2)^{\delta}]^{\frac{1}{\delta}}\}$$

where $\delta \in (1,\infty)$[33]. The coefficient of lower tail dependence is $\lambda^L = 0$, and the coefficient of the upper tail dependence is $\lambda^U = 2 - 2^{\frac{1}{\delta}}$. The implied Kendall's τ is $\frac{\delta-1}{\delta}$.

[33] Alternatively, δ can be defined as $\delta \in [1,\infty)$. When $\delta = 1$, we obtain the independence copula. Here we follow Patton (2013) and define the rang of δ as $\delta \in (1,\infty)$.

4. **SJC Copula (Archimedean)** The bivariate symmetrised Joe-Clayton (SJC) copula cdf is defined as:

$$C(u_1, u_2; \tau^U, \tau^L) = 1 - (1 - \{[1 - (1 - u_1)^k]^{-\gamma} + [1 - (1 - u_2)^k]^{-\gamma} - 1\}^{-\frac{1}{\gamma}})^{\frac{1}{k}}$$

where $k = 1/\log_2(2 - \lambda^U)$ and $\gamma = -1/\log_2(\lambda^L)$. The upper tail dependence λ^U and the lower tail dependence λ^L are defined as:

$$\lambda^U = \lim_{\delta \to 1} \Pr[U_1 > \delta | U_2 > \delta] = \lim_{\delta \to 1} \Pr[U_2 > \delta | U_1 > \delta] = \lim_{\delta \to 1} \frac{1 - 2\delta + C(\delta, \delta)}{1 - \delta}$$

$$\lambda^L = \lim_{\varepsilon \to 0} \Pr[U_1 \leq \varepsilon | U_2 \leq \varepsilon] = \lim_{\varepsilon \to 0} \Pr[U_2 \leq \varepsilon | U_1 \leq \varepsilon] = \lim_{\varepsilon \to 0} \frac{C(\varepsilon, \varepsilon)}{\varepsilon}$$

There is no implied Kendall's τ for SJC copula.

Regression Analysis with Bank CDS Returns

We include domestic bank CDS returns as one of the local factors and control for other determinants stated in eq(1.11). The domestic bank CDS spread is calculated as the average value of the Bank of China CDS spread, China Development Bank CDS spread and the Export-Import Bank of China CDS spread for the first three sub-periods. We include Industrial and Commercial Bank of China (ICBC) CDS to calculate the domestic bank CDS spread for the fourth period, since ICBC CDS data became avaliable on September 15, 2017.

Results show the coefficients on domestic bank CDS returns are statistically significant at the 1% level for all sub-periods. U.S. stock returns and the change in high-yield spread are two important global factors. The coefficients on the orthogonalized local stock market returns, the orthogonalized change in implied volatility, and the change in offshore exchange rate are all statistically significant at the 5% level during the U.S.-China trade war period. It indicates local factors play an important role in explaining sovereign CDS spread changes during the U.S.-China trade war period. Those results still in general confirm our empirical findings shown in Table 1.7.

Table A1.1: Regression Analysis with Domestic Bank CDS Returns

	Pre-Stock Market Turbulence	Stock Market Turbulence	Post-Stock Market Turbulence	U.S.-China Trade War
Δ Log(BCDS)	0.418***	0.212***	0.604***	0.757***
	(0.065)	(0.076)	(0.086)	(0.068)
U.S. Stock Return	−1.824***	−1.148***	−0.974***	−0.393**
	(0.284)	(0.167)	(0.180)	(0.184)
ΔInvestment	−0.047	0.347***	−0.030	0.057
	(0.040)	(0.118)	(0.032)	(0.080)
ΔHigh	0.151*	0.171***	0.064*	0.125*
	(0.086)	(0.048)	(0.036)	(0.068)
Local Stock Return	−0.701***	−0.355***	0.044	−0.239**
	(0.183)	(0.106)	(0.121)	(0.098)
Δ Implied Volatility	0.015	−0.007	0.049*	0.073**
	(0.055)	(0.026)	(0.025)	(0.034)
Δ FX	0.500	0.494	0.501	1.004***
	(1.364)	(0.438)	(0.379)	(0.376)
Δ Govt10yr	0.053	−8.905	2.904	−3.315
	(3.268)	(6.436)	(3.567)	(5.540)
Δ Slope	0.002	0.024	0.000	−0.005
	(0.005)	(0.020)	(0.002)	(0.012)
Bank Stock Return	−0.200	−0.065	−0.067	0.120
	(0.289)	(0.183)	(0.124)	(0.156)
Intercept	0.001	−0.000	−0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Obs	350	303	410	184
R^2	0.445	0.497	0.478	0.709

This table reports the estimation results of the regression of daily changes in the logarithm of China sovereign CDS rates on the daily changes in the logarithm of domestic bank CDS rates and other determinants stated in eq(1.11). Δ Log(BCDS) is the daily changes in the logarithm of domestic bank CDS spreads. U.S. stock returns are excess returns of MSCI USA index. ΔInvestment is the daily percentage changes in the difference between the S&P 500 BBB corporate bond yield and the S&P 500 AAA corporate bond yield. ΔHigh is the daily percentage changes in the difference between S&P 500 BB corporate bond yield and S&P 500 BBB corporate bond yield. Local stock returns are the orthogonalised daily percentage changes in the MSCI China index. ΔImplied Volatility is the orthogonalized daily percentage changes in VXFXI, which is the CBOE China ETF Volatility Index. ΔFX is the daily percentage changes in offshore exchange rate, which is expressed as units of Chinese Yuan per U.S. dollar. ΔGovt10yr is the daily percentage changes in China ten-year government bond yield. ΔSlope is the daily percentage changes in the difference between China ten-year and two-year government bond yields. Bank stock returns are the daily percentage changes in the self-constructed China bank index, which includes Hong Kong listed banks headquartered in mainland China. Robust standard errors are reported in parentheses.

*** Denotes significance at the 1% level.

** Denotes significance at the 5% level.

* Denotes significance at the 10% level.

Table A1.2:Credit Events, Deliverable Obligation Category, and Characteristics of China Sovereign CDS

Credit Events	Failure to Pay Repudiation/Moratorium Restructuring
Deliverable Obligation Category	Bond or Loan
Deliverable Obligation Characteristics	Specified Currency Not Sovereign Lender Not Domestic Law Not Domestic Issuance Maximum Maturity: 30 years Not Subordinated Assignable Loan Transferable Not Bearer

China Sovereign CDS: Credit Events, Deliverable Obligation Category, and Deliverable Obligation Characteristics

Table A1.2 shows the credit events, deliverable obligation category, and deliverable obligation characteristics of China sovereign credit default swap.

Deliverable Obligation Characteristics

- **Specified Currency:** Standard specified currencies are the Euro, U.S. dollar, Japanese yen, Canadian dollar, Swiss franc, and the British pound (Pan and Singleton, 2008).
- **Not Sovereign Lender:** An obligation not owed to a sovereign or supranational organization (including Paris Club debt). Supranational organizations include international or regional organizations, such as the following: the Asian Development Bank, the World Bank, the Bank for International Settlements, the International Monetary Fund, and the Basel Committee on Banking

Supervision. A list of supranational organizations' documents issued in 2017 can be found at International Actuarial Association. The lenders of loans, the borrower of which is the People's Republic of China, are mainly sovereign lenders (supranational organizations), such as the World Bank and the Asian Development Bank. Therefore, we do not consider them deliverable. The purpose of the loans is mainly for infrastructural or environmental projects. The detailed information of bonds and loans issued by People's Republic of China can be found via the Bloomberg terminal.

- **Not Domestic Law:** An obligation governed by the laws of the reference entity for sovereign CDS.

- **Not Domestic Issuance:** An obligation is qualified or registered to sale outside the domestic market. The domestic market refers to the market of reference entity.

- **Maximum Maturity of 30 Years:** The Maximum maturity of a deliverable obligation is 30 years, that is, any bond of maturity up to 30 years is considered deliverable.

- **Not Subordinated:** An obligation must not be subordinated to the most senior reference obligation in priority of payment, if none is specified, any unsubordinated borrowed money obligation.

- **Assignable Loan:** A loan that can be assigned or novated without the consent of the relevant reference entity or guarantor.

- **Transferable:** An obligation that can be transferable to commercial banks or financial institutions without any contractual, statutory, or regulatory restriction.

- **Not Bearer:** An obligation that is not a bearer instrument.[34]

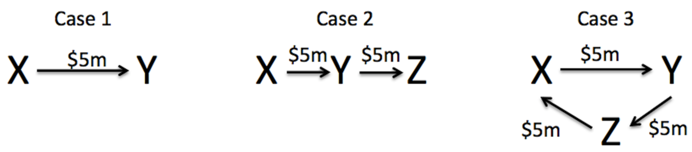
[34] A "deliverable obligation" refers to obligation that is not a bearer instrument unless the interests with respect to such bearer instrument are cleared via the Euroclear system, Clearstream International, or any other internationally recognized clearing system. Securities can be issued in either registered or bearer forms. "Bearer instrument" refers to the security in which no ownership is recorded, while "registered instrument" is the one in which issuing entity or firm keeps the record of the security's owner.

DTCC Single-Name CDS Net Notional Amount Outstanding

The DTCC reports market statistics on the top 1000 single-name CDS contracts. The DTCC net notional amount outstanding is widely used and considered, economically, the most meaningful measure of aggregate credit risk transfer (Augustin et al., 2016; Oehmke and Zawadowski, 2017). The net notional amount outstanding is calculated as the sum of net protection bought (or sold) by the net buyer (or seller).

We show three examples of how the net notional amount outstanding registered in the DTCC was generated by different CDS trading patterns. In case 1, Y bought \$5 million CDS protection directly from X. The net notional amount outstanding reported in DTCC was thus \$5 million. In case 2, Y bought \$5 million CDS protection from X. But this initial trade was offset by selling \$5 million CDS protect to Z. Therefore, the reported DTCC net notional amount outstanding was thus again \$5 million. In case 3, X bought \$5 million CDS protection from Z. In this way, Z's initial trade (bought from Y) was offset by selling \$5 million CDS protect back to X. Therefore, all three parties' trades were offset. This gave a net notional amount outstanding of \$0.

Figure A1.1 Net Notional Amount of CDS Outstanding



	Case 1		Case 2			Case 3		
	X	Y	X	Y	Z	X	Y	Z
Bought	0	5	0	5	5	5	5	5
Sold	5	0	5	5	0	5	5	5
Net	(5)	5	(5)	0	5	0	0	0
Case1: DTCC $5m			Case 2: DTCC $5m			Case 3: DTCC $0		

Monthly Regression Analysis: Additional Variables

1. **Domestic Debt/GDP.** General government domestic debt comprises the debt securities issued in the local market where the borrower resides. It is denominated in million U.S. dollars and collected from Bank for International Settlements (BIS). Domestic Debt/GDP is the ratio of general government domestic debt amount divided by GDP.

2. **International Debt/GDP.** General government international debt comprises the debt securities issued in a market other than the local market of the country where the borrower resides. It is denominated in million U.S. dollars and collected from BIS. International Debt/GDP is the ratio of China general government international debt amount divided by GDP.

3. **Current Account/GDP.** Current account balance as a percentage of GDP. The time series is obtained from the Organisation for Economic Co-operation and Development.

4. **Terms of Trade.** The monthly terms of trade data are directly obtained from Datastream.

Table A1.3: Monthly Regression with Additional Explanatory Variables

ΔLog(CDS)	(1)	(2)
ΔTerms of Trade	0.001	0.002
	(0.005)	(0.005)
ΔCurrent Account/GDP	−2.878	2.209
	(14.664)	(16.199)
ΔInternational Debt/GDP	−65.445	−69.247
	(62.815)	(62.409)
ΔDomestic Debt/GDP	1.586	2.542
	(2.241)	(2.492)
ΔRisk Premium	0.254	0.197
	(0.340)	(0.382)
ΔTerm Premium		1.609
		(2.396)
Intercept	0.001	−0.009
	(0.028)	(0.032)
Obs	64	58
R^2	0.025	0.032

This table reports the estimation results for monthly regression with additional explanatory variables. ΔLog(CDS) is the monthly changes in the logarithm of China sovereign CDS rates. Terms of trade is the monthly China terms of trade. Current Account/GDP stands for the China current account balance as a percentage of GDP. International Debt/GDP is the China general government international debt as a percentage of GDP. Domestic Debt/GDP is the China general government domestic debt as a percentage of GDP. Volatility risk premium is the difference between the VIX and Garman-Klass(1980) historical volatility of the S&P100 index. Term premium is constructed, following Longstaff et al. (2011) and Cochrane and Piazzesi (2005), as the expected excess returns on Treasury bonds represented as a linear function of one- through five-year forward rates. It is calculated using the monthly Fama-Bliss data from CRSP. The Fama-Bliss data are only avaliable up to December 2017, which yields a total 58 monthly data points. Robust standard errors are reported in parentheses.
*** Denotes significance at the 1% level.
** Denotes significance at the 5% level.
* Denotes significance at the 10% level.

5. **Term Premium.** The term premium is construed, following Longstaff et al. (2011) and Cochrane and Piazzesi (2005), as the expected excess returns on Treasury bonds represented as a linear function of one- through five-year forward rates. It is calculated using the monthly Fama-Bliss data from CRSP. Fama-Bliss data are avaliable up to December 2017, which yields 58 avaliable observations for regression analysis. The term premium has shown to be a less important factor in explaining the sovereign CDS spread changes (Longstaff et al., 2011).

6. **Volatility Risk Premium.**[35] Longstaff et al. (2011) suggests that volatility

[35]Bollerslev et al. (2011) provides an alternative volatility risk premium estimator. It yields similar estimation results as ours.

risk premium may represent a premium for bearing the volatility risk of an option position. Following the same method as them, the monthly volatility risk premium is calculated as the difference between the VIX and Garman-Klass (1980) historical volatility of the S&P 100 index. The historical volatility for date t is calculated using the open, high, low, and close (OHLC) prices from $t - 19$ to t (20-day period). The S&P 100 open, high, low, and close prices and VIX index data are collected from Bloomberg.

Additional Results of Tail Dependence Coefficient: Constant Volatility for ICBC

Table 1.2 Panel A shows that the null hypothesis of no ARCH effect cannot be rejected at the 5% significant level for ICBC CDS returns. Table 1.3 Panel A shows that α is insignificant for the ICBC CDS returns. Therefore, we use the constant volatility model as an alternative choice for the GARCH(1,1) conditional volatility model. We estimate the copula model based on the standardized residuals filtered by the constant volatility model. Table A1.4 shows the estimation results. The filtered standardized residuals pass LB, LM and CvM tests. The best selected copula model yields lower tail dependence coefficient. To be precise, the average tail dependence coefficient based on the GARCH(1,1) volatility model is 0.51, while the average tail dependence coefficient based on constant volatility model is 0.42. However, we prefer the GARCH(1,1) estimation results for the following two reasons. First, Table 1.3 Panel A shows that β is significant at 1% significant level, suggesting that the GARCH(1,1) model does capture additional information of GARCH part. Second, our conclusion holds still using both volatility models. Recall that our conclusion is that China sovereign CDS returns have a stronger tail dependence with commercial bank CDS returns than with policy bank CDS returns, and the results in Table 1.6 show that the annual tail dependence coefficients of policy banks do not exceed 0.10.

Figure A1.2: ICBC Constant Volatility Tail Dependence Coefficient

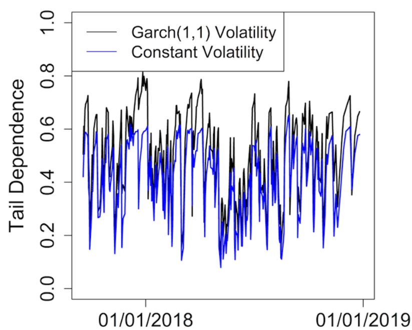


Table A1.4: Additional Results for ICBC: Constant Volatility

Panel A: Marginal Distribution and Goodness-of-Fit

	$Mean\_a_0$	$Variance$ $(constant$	v	ζ	$LB(10)$	$LM(10)$	$m1$	$m2$	$m3$	$m4$	CvM
	0.000 (0.001)	0.001	4.715** (0.905)	0.199** (0.068)	0.893	0.653	0.950	0.194	0.858	0.132	0.850

Panel B: Static and Dynamic Copulas: AIC and LL

	Static				ARMA				GAS		
	$Gaussian$ $(Static)$	$Gumbel$ $(Static)$	$Student's\ t$ $(Static)$	SJC $(Static)$	$Gaussian$ $(ARMA)$	$Gumbel$ $(ARMA)$	$Student's\ t$ $(ARMA)$	SJC $(ARMA)$	$Gaussian$ (GAS)	$Gumbel$ (GAS)	$Student's\ t$ (GAS)
AIC (LL)	−204.60 (103.30)	−205.18 (103.59)	−226.96 (115.48)	−219.60 (111.80)	−209.94 (107.97)	−225.94 (115.97)	−234.16 (121.08)	−232.56 (122.28)	−231.21 (118.60)	−234.74 (120.37)	***-246.44*** ***(127.22)***

Table A1.4 Panel A shows the estimated parameters of marginal distribution with constant volatility model for ICBC CDS returns. Standard errors are reported in parentheses. Residuals are checked for autocorrelation and ARCH effect using Ljung-Box test and Engel's LM test at lag10. The first four moments of $(\hat{u}\text{-}\bar{u})^j$ are used to check for i.i.d assumption. m1, m2, m3, m4 stand for the p-values of Ljung-Box test on the first four moments of $(\hat{u}\text{-}\bar{u})^j$ at lag10. The null hypothesis of uniform(0,1) distributed U is tested using CvM test. ** and * denote significance at the 1% and 5% level, respectively. Panel B reports the Akaike information criterion (AIC) and maximized log-likelihood (LL) of static and dynamic copulas for the sovereign CDS and ICBC CDS pair. Copula models include Gaussian copula, Gumbel copula, Student's t copula, and Symmetrised Joe-Clayton copula. Dynamic copulas include both ARMA and GAS types. Bold font denotes the selected copula formulation overall. The time period spans from September 15, 2017 to November 23, 2018.

2. The Information Content of Volatility for Sovereign CDS: Evidence from the Western European Market

Author: Yi Li*

Abstract: This paper studies the explanatory power of both country-level and market-level volatilities for Western European sovereign credit default swap (CDS) spreads during both the European sovereign debt crisis period and short-selling ban period. We include put option-implied volatility and Garman and Klass (1980) historical volatility as two volatility measures. The results show the changes in country-specific and market-level volatilities are important factors in explaining the sovereign CDS spread changes. Both country-level and market-level implied volatilities contain more information than historical volatilities in sovereign CDS pricing. We also find that the short-selling ban has a stronger impact in reducing the explanatory powers of the determinants of the sovereign CDS spreads for Austria, Belgium, France, Germany, and the Netherlands (non-GIIPS). This raises the question of whether there should be a universal ban on short selling. We use Sweden sovereign CDS for a robustness check. Our results confirm the important role of country-specific and market-level option-implied volatilities for sovereign CDS spreads.

Keywords: Western European Sovereign CDS; Option-implied volatility; Garman and Klass (1980) historical volatility; European sovereign debt crisis; 2012 EU permanent short-selling ban

JEL Classification: G01, G10, G12, G18

*I am grateful for the valuable comments and suggestions received from Angelo Ranaldo, Paul Söderlind, and the seminar participants at the St. Gallen university.

2.1 Introduction

The recent European sovereign debt crisis has fueled interest in the European sovereign credit default swap (CDS) market, which, as a consequence of the crisis, has become more liquid and less obscure (Blommestein et al., 2016; Dieckmann and Plank, 2012). This dramatic development of the sovereign CDS market calls for a better understanding of the pricing of European sovereign credit risk. Here, the sovereign CDS contract was blamed for being used by speculators to manipulate the sovereign borrowing costs and destabilizing the European financial market during the crisis. To prevent a disorderly market and possible systemic risk caused by an unregulated short-selling instrument[1], the 2012 EU permanent short-selling ban went into effect on November 01, 2012. It is the most prominent regulation aimed at harmonizing the short-selling and CDS trading rules (International Monetary Fund, 2013). This change in European sovereign CDS trading regulation motivates us further to study the impact of the 2012 EU permanent short-selling ban on the determinants of European sovereign CDS spreads.

Our understanding of the role of country-level volatility in determining sovereign CDS spreads remains limited, while the important role of firm-level volatility in determining the corporate CDS spreads has been well documented in the literature (Cao et al., 2010; Tang and Yang, 2008). Our paper attempts to shed new light on the explanatory power of country-specific volatility for sovereign CDS spreads. However, to access the pure explanatory power of country-level volatility, we need a variable that is independent of market-level volatility. We adopt a well documented orthogonalized method from Dieckmann and Plank (2012) and Blommestein et al. (2016) to obtain this variable. By creating this orthogonalized country-specific volatility, we can include both orthogonalized country-specific volatility and market volatility in our regression analysis and test their explanatory powers for sovereign CDS spreads[2]. Moreover, because we are also interested in studying the impact of

[1]This view of short selling can lead to an excessive downward spiral in prices, leading to a disorderly market and possible systemic risk; this thought is shared in a European Commission (2010) document: "Proposal for a regulation of the European parliament and of the council on short selling and certain aspects of credit default swaps."

[2]Using an orthogonalized series solves the multicollinearity problem, which arises when including two highly correlated variables in the regression (Blommestein et al., 2016). In our case, the nonorthogonalized country-specific volatility and European market volatility are highly correlated. For instance, the Pearson's

the 2012 EU permanent short-selling ban, we can now perform a regression analysis to test the explanatory powers of both country-specific and market-level volatilities before and after the ban.

We use the current paper to shed new light on the explanatory powers of both country-level volatility and market-level volatility on European sovereign CDS spreads before and after the short-selling ban. Sovereign CDS papers typically use close-to-close historical volatility or the GRACH(1,1) volatility estimator to explain the sovereign CDS spread changes, often finding it to be a useless factor (Dieckmann and Plank, 2012; Fontana and Scheicher, 2016). We improve the volatility measure by considering both the option-implied volatility and Garman and Klass (1980) historical volatility. The Garman and Klass (1980) historical volatility is 7.4 times more efficient than the traditional close-to-close estimator (Garman and Klass, 1980). Although the role of option-implied volatility has not been well investigated in the sovereign CDS literature, Cremer et al. (2008) and Cao et al. (2010) have shown option-implied volatility is an important factor in explaining the variation in corporate credit spreads. To investigate whether our volatility variables provide additional explanatory power, we include more local, regional, and global variables to control for other determinants. The results of those determinants also allow us to check whether they are consistent with the empirical findings from the literature.

We address the following questions in the current paper: first, do the changes in country-specific and market volatilities have explanatory power for sovereign CDS spread changes? We measure the country-level and market-level volatilities using both the 30-day at-the-money put option-implied volatility and Garman and Klass (1980) historical volatility. Second, does the option-implied volatility outperform the historical volatility in explaining the sovereign CDS spread changes? Cao et al. (2010) show that the option-implied volatility dominates the historical volatility in explaining the time-series variation in corporate CDS spreads. We perform the country-by-country time series regression for both option-implied volatility and the

pairwise correlation coefficient between nonorthogonalized France CAC40 30-day put option-implied volatility and EuroStoxx 50 30-day put option-implied volatility is 0.98 in levels and 0.95 in changes. The Pearson's pairwise correlation coefficient between nonorthogonalized Italy FTSEMIB 30-day put option-implied volatility and EuroStoxx 50 30-day put option-implied volatility is 0.92 in levels and 0.71 in changes. The data and sample period we used for calculating the correlation coefficients are the same as the ones we used to carry out our core analysis and is described in Sections 2.2.2 and 2.2.5.

Garman and Klass (1980) historical volatility to address this second question. We expect both country-specific and market option-implied volatilities to outperform the country-specific and market historical volatilities. Third, what is the impact of the 2012 EU short-selling ban on the explanatory powers of those variables?

Our analysis brings new insights to academics, investors, and policymakers. On the academic side, our work highlights the important role of country-specific volatility and market-level volatility in pricing sovereign credit risk. Moreover, the sovereign CDS literature typically uses historical volatility rather than option-implied volatility as one of the explanatory variables to analyze CDS spreads (Dieckmann and Plank, 2012; Fontana and Scheicher, 2016). Our results show that the option-implied volatility outperforms historical volatility. This suggests that the option-implied volatility should be used in future studies on sovereign CDS pricing. For investors, our results suggest the country-specific volatility index and market volatility index are good indicators to monitor sovereign credit risk. For policymakers, our results on the short-selling ban show most variables lose their explanatory powers for sovereign CDS spreads after the ban. This is especially true for Austria, Belgium, France, Germany, and the Netherlands (non-GIIPS). This significant loss of the variables' explanatory powers, especially for non-GIIPS countries, brings into question whether there should be such a universal ban on short selling[3].

We use a comprehensive data set of Credit Market Analysis (CMA) sovereign CDS quotes of Western European countries and put options on those countries' premier stock market indices to perform our analysis. We perform our analysis on the European sovereign CDS market because we focus on the role of country-level and market-level volatilities in pricing sovereign credit risk for the European sovereign debt crisis period and EU short-selling ban period. We choose Western European CDS contracts because they have options on their premier stock market indices. We choose put option data because both put options and CDS contracts are instruments for hedging against the downside risk. The put option-implied volatility is also used in the literature as an important factor in explaining the variation in corporate credit spreads (Cao et al., 2010; Cremers et al., 2008). In summary, we include eight

[3]The 2012 permanent EU short-selling ban involves 30 sovereigns across 27 countries in the European Economic Area (EEA) plus Norway, Iceland, and Liechtenstein, and applies to all market participants, including those transactions concluded outside the EEA (International Monetary Fund, 2013).

Western European sovereign CDS contracts. All eight countries have option data on their premier stock market indices. The full sample period is from July 01, 2009 to August 10, 2015. We use July 01, 2009 as the start date to avoid any overlap with the financial crisis period and the potential structural break caused by the CDS "Small Bang." The full sample period is separated into two sub-periods using the implementation date of the 2012 permanent EU short-selling ban. This allows us to study the explanatory power of the determinants of European sovereign CDS spreads before and after the ban.

For each country, we build two country-level volatility measures: the 30-day at-the-money put option-implied volatility and Garman and Klass (1980) historical volatility. The underlying equity index of the put option is each country's premier stock market index. Daily option data are collected from Bloomberg. The country-specific Garman and Klass (1980) historical volatility is calculated using the daily high, low, open, and close prices of each country's premier stock market index. Similarly, we construct the option-implied volatility and Garman and Klass (1980) historical volatility for the European market. The market-level option-implied volatility is the EuroStoxx 50 30-day at-the-money put option-implied volatility collected from Bloomberg. The market-level Garman and Klass (1980) historical volatility is calculated using the daily high, low, open, and close prices of EuroStoxx 50. To test whether the change in country-specific volatility is an important factor in explaining sovereign CDS spread changes, we need to use orthogonalized series. We orthogonalize the country-specific volatility by regressing the percentage change in the country-specific volatility on the percentage change in the market volatility. The sum of the intercept and residuals is used to construct this orthogonalized variable.

We include six additional variables to test whether the change in country-level and market-level volatilities provides additional explanatory power for sovereign CDS spread changes. Those six additional variables include two domestic variables, three regional variables, and one global variable. The two domestic variables are local financial index returns and local stock market index returns. Both series are orthogonalized following Blommestein et al. (2016) and Dieckmann and Plank (2012). To be specific, the orthogonalized local financial index returns are constructed as the sum of intercept and residuals from a regression of local financial index returns on world financial index returns and domestic stock market returns. The orthogonalized local equity index returns are calculated as the sum of intercept and residuals from a regression of domestic stock market returns on EuroStoxx 50 returns. The three regional variables are the change in forex, slope of yield curve, and exchange rate uncertainty. Forex is the exchange rate expressed as units of U.S. dollar per Euro. The slope of yield curve is the difference between the German ten-year government bond yield and two-year yield. The exchange rate uncertainty is captured by the "Euro VIX" (EVZ). It is orthogonalized to separate the uncertainty embedded in foreign exchange market from the uncertainty embedded in the stock market. The global variable is the change in U.S. high-yield spread, which is calculated as the yield spread between S&P 500 BB corporate bond yield and S&P 500 BBB corporate bond yield.

Our first hypothesis is that country-specific option-implied volatility is an important factor and that it outperforms country-specific historical volatility in explaining the sovereign CDS spread changes. Merton's (1974) structural model suggests asset volatility is an important primitive variable for determining the default probability and, consequently, the spread. Tang and Yang (2008) use the individual firm's at-the-money stock option-implied volatility as the proxy for asset volatility to study the variation in corporate CDS spreads; they suggest asset volatility should be approximately proportional to stock volatility in a simplified framework. Cao et al. (2010) show an individual firm's put option-implied volatility is an important factor in explaining the time-series variation in corporate CDS spreads. Although the sovereign CDS literature recognizes the important role of country-level volatility in the determination of sovereign CDS spreads, most studies typically use the close-to-close historical volatility or GRACH(1,1) volatility estimator to explain the sovereign CDS spread changes, often finding it to be a useless factor (Dieckmann and Plank, 2012; Fontana and Scheicher, 2016). Moreover, option-implied volatility has shown to be an important factor for determining corporate CDS prices. Cao et al. (2010) and Cremer et al. (2008) show that the option-implied volatility denominates historical volatility in explaining variation in corporate credit spreads. Therefore, we build our first hypothesis based on the theory and empirical findings in the field of corporate credit spreads: country-specific option-implied volatility is an important factor and outperforms country-specific historical volatility in explaining the sovereign CDS spread changes.

To build our hypothesis on market volatility, we first observe there is a strong co-movement in sovereign CDS spreads, as shown in Figure 2.1. If market volatility does have an explanatory power for sovereign CDS spreads, it should be a meaningful factor underlying such a commonality. To investigate this issue, we perform a principal component analysis of daily CDS spread changes. We extract the first principal component and regress it on the regional and global factors. The results show the coefficients on market implied volatility and market historical volatility are both statistically significant. However, the factor loadings on market implied volatility is much larger than the loading on market historical volatility. Together with the evidence from the literature that shows option-implied volatility dominates historical volatility in explaining the time-series variation in corporate CDS spreads (Cao et al., 2010), we formulate our second hypothesis: market volatility is an important factor, and market option-implied volatility outperforms the market historical volatility in explaining the sovereign CDS spread changes.

Our third hypothesis relates to the short-selling ban. Che and Sethi (2012) examine the effects of speculation using "naked" CDS protection; they show when buying "naked" CDS is allowed, there will be an increase in the cost of debt, and the rollover risk will be exacerbated. Their model suggests a ban on short-selling would bring stability to the financial market. However, the empirical findings of a ban on short-selling in equity market does not find such a benefit. Beber and Pagano (2013) show the short-selling ban in equity markets reduces market liquidity, increases price volatility, and hinders price discovery. We investigate the outstanding amount of Western European sovereign CDS contracts and find the total amount decreased around 23.6% within one year after the implementation of 2012 EU permanent short-selling ban[4]. This suggests a dramatic decline in the market liquidity of European sovereign CDS after the ban. Moreover, our results of the principal component analysis show that the degree of commonality in Western European sovereign CDS spreads decreased after the short-selling ban. For instance, the first principal component alone can explain 80.14% of the variation in European sovereign debt crisis period, while the first principal component alone can only explain 51.46%

[4]The total net notional amount of European Sovereign CDS outstanding from 2009 to 2015 is stated in Appendix Table A2.1. There is a clear decrease in the total amount after the short-selling ban, which was implemented on November 01, 2012. To be specific, the annual total amount decreased from 88.9 billion U.S. dollars in 2012 to 67.9 billion U.S. dollars in 2013.

of the variation in the short-selling ban period. The declined cross-section correlation in the short-selling ban period suggests a possible impact of the short-selling ban on the explanatory variables. Figure 2.1 shows that the sovereign CDS spreads remained at low levels after the implementation of short-selling ban. This is especially true for non-GIIPS countries. For instance, the average five-year CDS spreads of France was 105.42 bps before the ban and 56.02 bps after the ban. Therefore, the short-selling ban seems to have a larger impact on non-GIIPS countries. Based on the above empirical findings, we formulate our third hypothesis: if the short-selling ban does have an impact on the explanatory powers of the determinants of sovereign CDS spread changes, we expect this effect to be stronger for non-GIIPS countries.

We perform the country-specific time series regressions for both the European sovereign debt crisis period and short-selling ban period. A time series analysis allows us to test the explanatory powers of both country-level volatility and market-level volatility. By regressing the daily changes in the logarithm of sovereign CDS rates on the change in market volatility and orthogonalized change in country-specific volatility, we obtain our results for the baseline regression. Both the option-implied volatility and Garman and Klass (1980) historical volatility are used for measuring country-specific volatility and market-level volatility. We perform this baseline regression for all eight Western European countries for both the European sovereign debt crisis period and short-selling ban period. To test whether our volatility variables provide additional explanatory power, we further include six local, regional, and global variables. We perform the country-by-country time series regression with those additional variables for both the European sovereign debt crisis period and short-selling ban period. The estimation results allow us to test whether the changes in country-level and market-level volatilities remain important factors in explaining the sovereign CDS changes. Moreover, we can also check the signs of the coefficients to see whether they are consistent with economic intuition and the empirical findings from the literature.

Our results show the orthogonalized change in country-specific option-implied volatility is an important factor for the sovereign CDS spread changes for almost all countries during the crisis period, while the orthogonalized change in the Garman and Klass (1980) historical volatility only has explanatory power for the sovereign CDS spread changes of distressed economies. Turning to the short-selling ban period, the coefficients of the orthogonalized change in country-specific option-implied volatility become statistically insignificant for all non-GIIPS countries, but it still remains an important factor in explaining the sovereign CDS spread changes of distressed economies. The orthogonalized change in the Garman and Klass (1980) historical volatility has no explanatory power for all eight countries in the short-selling ban period. These results confirm our first hypothesis on the country-level option-implied volatility.

The results on the market volatility show the change in market volatility, both option-implied and Garman and Klass (1980) historical volatilities, is an important factor in explaining the sovereign CDS spread changes for all eight countries during the crisis period. However, the factor loadings on historical volatility are much smaller than the loadings on implied volatility. This means the economic significance of market historical volatility is rather weak. Turning to the short-selling ban period, the coefficients on the change in market implied volatility are statistically significant for all eight countries, while the coefficients on the change in market historical volatility are statistically significant for five out of eight countries. Those results confirm our second hypothesis about the market volatility.

Turning to the effect of the short-selling ban on country-level and market-level volatilities, our results show a few aspects. First, the coefficients on the orthogonalized change in country-specific implied volatility are statistically significant for almost all countries during the crisis period. It remains an important factor for three distressed countries, namely Italy, Spain, and Greece, during the short-selling ban period, while the coefficients become statistically insignificant for all five non-GIIPS countries. Our results for market volatility show the estimated factor loadings on the change in market option-implied volatility of the five non-GIIPS countries become much smaller during the short-selling ban period. These results suggest the short-selling ban does have an impact on the explanatory power of country-specific and market volatilities, and this impact is stronger for non-GIIPS countries. Turning to the effect of the short-selling ban on the six additional control variables. The coefficients on the change in the slope of yield curve and U.S. high-yield spread remain to be statistically significant for Italy and Spain during the short-selling ban period, while the coefficients for the regional and global variables become statically insignificant for most non-GIIPS countries during the short-selling ban period. Overall, the above results for the country-specific volatility, market volatility, and additional control variables during the short-selling ban period confirm our third hypothesis.

We also perform a robustness check on the explanatory power of country-level and market-level implied volatilities using the five-year sovereign CDS spreads of Sweden and the put option data of Sweden's premier stock market index (OMXS30). The country-level implied volatility is the 30-day at-the-money put option-implied volatility of the OMXS30. The market option-implied volatility is the EuroStoxx 50 30-day at-the-money put option-implied volatility. To test whether the change in country-level and market-level implied volatility provides additional explanatory power for Sweden sovereign CDS spread changes, we control for six additional variables. These control variables are the local stock market returns, local Morgan Stanley Capital International (MSCI) Financial index returns and the change in exchange rate, one-month FX implied volatility of USD/SEK, U.S. high-yield spread, and slope of yield curve. Local stock market returns, MSCI Financial index returns and the change in one-month FX implied volatility are orthogonalized series, which are constructed using the same method discussed in Section 2.2.4. The results show market implied volatility is an important factor in both periods, and the country-specific implied volatility is an important factor during the crisis period. This result is similar to the results of the non-GIIPS countries, such as Germany. Nevertheless, the results of our robustness check confirm the explanatory power of both country-specific and market-level option-implied volatilities for sovereign CDS spreads.

We contribute to three strands of the literature. First, we contribute to the early literature on the information content of implied volatility for credit spreads. Merton's (1974) structural model sets the foundation for the role of asset volatility in determining the default probability and, consequently, the spread. Tang and Yang (2008) suggest that asset volatility should be approximately proportional to stock volatility in a simplified framework. Their paper show an individual firm's at-the-money stock option-implied volatility is an important factor in explaining the variation in corporate CDS spreads. Cao et al. (2010) shows individual firm's put option-implied volatility is an important factor and denominates historical volatility in explaining the time-series variation in corporate CDS spreads. Cremer et al. (2008) show an individual stock option-implied volatility contains more useful information than the historical volatility for credit spreads. Sovereign CDS papers typically use the close-to-close historical volatility or GRACH(1,1) volatility estimator to explain the sovereign CDS spread changes, often finding it to be a useless factor (Dieckmann and Plank, 2012; Fontana and Scheicher, 2016). Wang et al. (2012) use the option-implied volatility as one of the volatility estimates to study the sovereign CDS spread levels. We add to this literature by providing the first study to test the explanatory power of the change in option-implied volatility, both at the country and market levels, for sovereign CDS spread changes. We also show that the implied volatility contains more information for sovereign CDS spreads than the Garman and Klass (1980) historical volatility.

Second, we provide empirical evidence to the literature on the effect of the short-selling ban. Che and Sethi's (2012) model suggests the ban on buying "naked" CDS stabilizes the financial market, decreases the cost of debt, and reduces the rollover risk. However, Beber and Pagano (2013) show the short-selling ban in equity markets reduces market liquidity, increases price volatility, and hinders price discovery. Our empirical findings support the view of Beber and Pagano (2013). We find most determinants lost their explanatory power after the implementation of 2012 EU permanent short-selling ban. This significant loss in the variables' explanatory powers is especially true for non-GIIPS countries, which brings up the question of whether there should be such a universal ban on short selling. We also find a dramatic decline in market liquidity of European sovereign CDS after the ban by using a net notional amount of outstanding data.

Third, we add to the literature on the source of commonality in sovereign CDS spreads. Longstaff et al. (2011) show the first principal component can explain 65% of the variation in the 26 developed and emerging-market countries' sovereign CDS spreads during the 2000-2010 sample period. This value increases to 75% during the 2007-2010 crisis period. The factors underlying this commonality are global variables such as U.S. stock market returns and the change in the spreads of U.S. high-yield corporate bonds. Dieckmann and Plank (2012) show that a first principal component can explain 75% of advanced economies' sovereign CDS spreads. They find the state of the global financial sector is important in understanding such commonality. We add to this literature by considering the market volatility as a meaningful factor behind this commonality. We perform a principal component analysis using the daily sovereign CDS spread changes, extract the first principal component, and regress it on the market volatility and other regional and global factors. The results show the coefficients on the change in market volatility are statistically significant in both periods.

There is another stand of the literature on volatility risk premium. Cao et al. (2010) measure volatility risk premium as the difference between the implied volatility and predicted value of 84-day future realized volatility, finding that the volatility risk premium embedded in option prices covaries with corporate CDS spreads. Longstaff et al. (2011) measure the volatility risk premium as the difference between CBOE volatility index (VIX) and the realized volatility of the Standard & Poor's (S&P) 100 index. Their realized volatility is calculated using the 20-day historical prices from $t-19$ to t. They use the volatility risk premium as one of the risk premium proxies to study the sovereign CDS spreads. Although this paper includes two types of volatility measures, our goal is to test the explanatory power of the implied volatility and historical volatility individually for sovereign CDS spreads. To be specific, we try to show country-level and market-level volatilities are important factors for sovereign CDS spreads and that they are better measured by option-implied volatility rather than historical volatility. By doing so, we aim to provide evidence for future studies that use the country-specific and market option-implied volatilities for sovereign CDS pricing. Therefore, we do not relate our paper to the literature on volatility risk premium.

The remainder of the current paper is organised as follows: Section 2 describes the mechanics of the CDS market and describes the data; Section 3 describes the modeling framework; Section 4 summarizes results; Section 5 provides a robustness check; Section 6 presents concluding remarks.

2.2 Data Description

2.2.1 The Western European Sovereign CDS Market

A sovereign CDS is a fixed income derivative instrument and performs much like insurance against the future credit events of the underlying reference entity. The standard Western European sovereign CDS contract covers the following credit events: failure to pay, restructuring, and repudiation/moratorium. Unlike the emerging European sovereign CDS contract, there is no grace period extension applicable to the "failure to pay" covered in the standard Western European sovereign CDS contracts. The restructuring clause for the Western European sovereign CDS contract is "full-restructuring." This means any bond with a maturity up to 30 years is considered deliverable[5]. The contract's denominated currency is the major difference between sovereign CDS and corporate CDS. The market convention is to trade USD−denominated European sovereign CDS contracts[6]. Those contracts are the most liquid ones in the market. Cash settlement auctions have been incorporated into the standard CDS document by International Swaps and Derivatives Association (ISDA) since the 2009 CDS "Big Bang." The main advantage of a cash settlement is that it reduces the potential for heightening the underlying bond market's volatility caused by "naked" CDS buyers[7]. Although the European sovereign CDS market has grown rapidly since 2008 (International Monetary Fund, 2013), its size is relatively small compared with the underlying sovereign debt market. For instance, the ratio of Greek CDS net notional amount outstanding over the amount of debt outstanding (coverage ratio) has never exceeded 3% for the July 2009 to December 2015 period[8]. The coverage ratios[9] for Italy, France, and Germany remain stable and below 2%. This indicates that CDS rate manipulation from the demand-based price pressure can only have a marginal impact on the sovereign credit risk born by bond owners

[5]The deliverable obligations need to be denominated in one of the "standard specified currencies": U.S. dollar, Euro, Swiss franc, British pound, Canadian dollar, or Japanese yen.

[6]The rationale behind this is to separate sovereign risk from the contract's payment. Sovereign CDS contract denominated in local currency will harm the wealth of foreign investors mostly because of the depreciation of local currency in the case of a credit event, but it still holds some value for the domestic CDS holders. There are sovereign contracts that quote the local currency as well. Some papers investigate the "Quanto CDS" spreads, which are the difference in premiums of those CDS contracts with the same underlying reference entity but are denominated in a different currency. See, for example, Augustin et al. (2018) and Pu and Zhang (2012b).

[7]The "naked" CDS buyer needs to buy bonds from the market in the case of compulsory physical settlement. This action would drive up the bond price, heighten its volatility, and cause a "short squeeze" in the underlying cash market. "Short squeeze" refers to the wealth transfer from the "naked" CDS buyers to the bondholders who do not hold CDS protection.

[8]This result is consistent with the findings of Duffie (2010), which show the net Greek CDS position remained well under 3% of the total amount of Greek debt outstanding.

[9]To calculate the coverage ratio, we collect the net notional amount outstanding from Depository Trust & Clearing Corporation (DTCC) and the amount of debt outstanding from Bloomberg. We do not report the table of coverage ratios in this paper. It can be provided upon request.

and CDS sellers (Duffie, 2010).

There are two major regulatory changes[10] in the Western European sovereign CDS market: the CDS "Small Bang," and the 2012 permanent EU short-selling ban. The CDS "Small Bang" was implemented on June 20, 2009. It entails convention changes related to Western European sovereign CDS trades and to European corporate CDS trades. One of the major changes is related to the quoting conventions and coupons. Starting from June 20, 2009, the standard Western European sovereign CDS contracts were traded with fixed coupons such as 25 bps or 100 bps. The difference related to the running spread was settled through an upfront payment. The primary goal of this change was to improve the efficiency and transparency of the CDS market. The second major regulatory changes in the Western European sovereign CDS market is the 2012 permanent EU short-selling ban, which came into force on November 01, 2012. It involved 30 sovereigns, across 27 countries in the EEA, plus Norway, Iceland, and Liechtenstein, and applies to all market participants, including those transactions concluded outside the EEA (International Monetary Fund, 2013).

2.2.2 Data

We include eight five-year USD−denominated[11] Western European sovereign CDS contracts in our study. U.S. dollar is the standard currency in the Western European sovereign CDS market (Dieckmann and Plank, 2011). All eight countries are EU members, and all of them have adopted the euro as their domestic currencies. To

[10]We acknowledge the temporary ban on trading "naked" CDS in Germany from May 19, 2010 to March 21, 2011. This 2010 temporary short-selling ban involved all Euro area sovereigns but only applied to the transactions concluded in Germany. Pu and Zhang (2012a) study the global impact of the 2010 German short-sale ban. They show that the temporary ban did not effectively suppress the rise of sovereign CDS spreads in the crisis region. Figure 2.1 confirms the findings in Pu and Zhang (2012a) and also shows a clear effect of the 2012 permanent EU short-selling ban on stabilizing and decreasing the Western European sovereign CDS spreads, especially for five non-GIIPS countries. Moreover, the 2012 permanent EU short-selling ban applied to all market participants, including those transactions concluded outside the EEA. The 2010 temporary ban only applied to the transactions concluded in Germany. Because of the marginal impact of the 2010 temporary ban, we only consider the 2012 permanent EU short-selling ban in our paper.

[11]A sovereign CDS contract is typically denominated in a different currency other than its domestic currency. Western European sovereign CDS contracts are typically denominated in USD rather than the euro. The rationale behind this can be found in Section 2.2.1.

Table 2.1 – Variable Definitions

Panel A: Description of Equity Indices and Volatilities			
Country	Equity Index (Bloomberg Ticker)	Option-Implied	Garman and Klass (1980)
France	CAC 40 equity index (CAC40)	✓	✓
Germany	Deutsche Boerse AG German stock index (DAX)	✓	✓
Austria	Vienna stock exchange Austrian traded index (ATX)	✓	✓
Netherlands	AEX equity index (AEX)	✓	✓
Belgium	BEL 20 equity index (BEL20)	✓	✓
Italy	FTSE MIB equity index (FTSEMIB)	✓	✓
Spain	IBEX 35 equity index (IBEX)		✓
	MSCI Spain index (MXES)	✓	
Greece	FTSE/Athens stock exchange large cap index (FTASE)	✓	✓

Panel B: Description of Variables			
Variables	Definition	Source	Sign
Country-specific Volatility	Orthogonalized 30-day at-the-money put option-implied volatility; Orthogonalized Garman and Klass (1980) historical volatility (Orthogonalization method, see Section 2.2.4)	Bloomberg and Self-Calculation	+
Market Volatility	EuroStoxx 50 30-day at-the-money put option-implied volatility; Garman and Klass (1980) historical volatility	Bloomberg and Self-Calculation	+
Forex	Exchange rate expressed as units of U.S. dollar per Euro	Datastream	−
Local Financial Returns	Orthogonalized MSCI Financial index returns. (Intercept and residuals from a regression on MSCI World Financial index returns and domestic stock market index returns. MSCI World Financial index returns are the intercept and residuals from a regression on EuroStoxx 50 returns (Dieckmann and Plank, 2012))	Bloomberg, Datastream, and Self-Calculation	−
Local Stock Market Returns	Orthogonalized national equity index returns (Panel A) (Intercept and residuals from a regression on EuroStoxx 50 returns)	Bloomberg and Self-Calculation	−
Slope	Difference between the ten-year German bond yield and the two-year yield (Collin-Dufresne et al., 2001)	Bloomberg and Self-Calculation	−
EVZ	Orthogonalized "Euro VIX"(Intercept and residuals from a regression on the percentage changes in EuroStoxx 50 30-day at-the-money put option-implied volatility)	Bloomberg and Self-Calculation	+
High	Yield spread between S&P 500 BB and S&P 500 BBB corporate bond yields.	S&P	+

This table provides the definitions of the variables used in our analysis. Panel A shows the information of each country's premier stock market index (with corresponding Bloomberg ticker). "Option-Implied" and "Garman and Klass (1980)" refer to the 30-day at-the-money put option-implied volatility and Garman and Klass (1980) historical volatility. ✓ indicates that the 30-day at-the-money put option-implied volatility or Garman and Klass (1980) historical volatility are available/calculated for the corresponding stock market index. Panel B provides the definitions of covariates used in our regression analysis. For each variable, we also show the corresponding data source and the expected sign. The country-specific volatility, local financial returns, and local stock market returns are country-specific variables. Market volatility, forex, slope of yield curve, EVZ (exchange rate uncertainty), and U.S. high-yield spread are regional and global variables. A detailed explanation about the orthogonalization method can be found in Section 2.2.4.

be precise, we include the five-year sovereign CDS spreads of Austria, Belgium, France, Germany, Greece, Italy, the Netherlands, and Spain. We do not include other Western European sovereign CDS contracts because of the lack of option data on their premier stock market indices. We collect the daily sovereign CDS bid and ask quotes from CMA and compute the mid-quotes as the average of bid and ask[12]. CMA aggregates the quotes from a minimum of three distinct sell side members and is widely used as a CDS data source. See, for example, Avino and Cotter (2014), Kallestrup et al. (2016), and Meine et al. (2018). Although CMA provides the end-of-day full sovereign CDS curve for the standard Western European sovereign CDS contract, we use the five-year sovereign CDS spreads to perform our analysis by following Longstaff et al. (2011), Eyssell et al. (2013), Pu and Zhang (2012a), and Wang et al. (2012). The full sample period is from July 01, 2009 to August 10, 2015, which is separated into two sub-periods: European sovereign debt crisis period from July 01, 2009 to October 31, 2012, and the short-selling ban period from November 01, 2012 to August 10, 2015. The detailed description of our sample periods can be found in Section 2.2.5. CMA reports missing Greek CDS data from March 12, 2012 to April 10, 2012 around the first Greek event. The discontinuous Greek CDS data are also shown from March 01, 2013 to May 20, 2013. There are two Greek events that happened during our full sample period. One happened in the European sovereign debt crisis period and the other in the short-selling ban period. We explain why our regression results are not affected by those two Greek events in Section 2.2.6.

We use two types of volatility measures, option-implied volatility and historical volatility, as the proxies for the state of the economy. For each country, the option-implied volatility is the 30-day[13] at-the-money put option-implied volatility written on its premier stock market index. We choose the put option because both the CDS contract and put option are instruments for hedging against the downside risk. To be

[12]To further ensure the accuracy of our CDS data, we use additional daily quotes from CMA Intraday. Both CMA and CMA Intraday provide daily quotes for five-year USD-denominated Western European sovereign CDS contracts. The difference is that CMA Intraday also provides other types of CDS quotes, such as high, low, and open quotes besides close. Our CDS data are accurate because they have the same values as the closing mid-quotes reported by CMA Intraday.

[13]Bloomberg also provides at-the-money put option-implied volatility for other constant maturities, such as two and three months. We choose the 30-day option-implied volatility because it is the only series that provides continuous data for Greece.

precise, we collect the daily 30-day at-the-money put option-implied volatility for France (CAC40), Germany (DAX), Austria (ATX), the Netherlands (AEX), Belgium (BEL20), Italy (FTSE MIB), and Greece (FTASE) from Bloomberg. For Spain, we use the 30-day at-the-money put option-implied volatility of U.S. traded options on iShares MSCI Spain exchange-traded fund (ETF) because we fail to find enough option data on its premier stock market index (IBEX35)[14]. The U.S. traded options on iShares ETF for a country's MSCI index is often considered an alternative choice if the options for the country's premier stock market index is not avaliable (Kelly et al., 2016). Datastream also provides option-implied volatility data for European premier stock market indices. However, we do not consider them because of the limited data availability. For instance, Datastream's put option-implied volatility data for Austria (ATX), Greece (FTASE), and Belgium (BEL20) are only avaliable from February 2014 to August 2015, July 2013 to August 2015, and December 2010 to August 2015.

The historical volatility measure is the Garman and Klass (1980) volatility estimator. It is a range-based volatility estimator that extends Parkinson's (1980) volatility estimator by incorporating open and close prices but still assuming zero drift for the pricing process. The Garman and Klass (1980) historical volatility is 7.4 times more efficient than the traditional close-to-close estimator (Garman and Klass, 1980). Another reason for choosing the Garman and Klass (1980) volatility estimator is that it outperforms the EGARCH(1,1) volatility and the Pareto distribution's scale parameter[15]. For each country, we calculate the Garman and Klass (1980) historical

[14]Wang et al. (2012) suggest Bloomberg also provides implied volatility for Finland's HEX25 index. Kelly et al. (2016) also indicate the option-implied volatility of Spain's premier stock market index (IBEX35) is avaliable although their option data source is OptionMetrics. However, we fail to find enough/avaliable data for both series from Bloomberg. For the put option-implied volatility of BEL20 (Belgium), there are missing values for 2012-2013. We fill them using the 30-day at-the-money put option-implied volatility from Datastream.

[15]Our unreported results show the generalized Pareto distribution's scale parameter captures neither the country-level risk nor market-level risk. Moreover, we test the explanatory power of rolling EGARCH(1,1) volatility, which is calculated as the daily forecast of EGARCH(1,1) volatility using ten-year daily equity returns as input and 252 days' forecast volatility as the output. The daily historical volatility is calculated as the average value of the 252 predicted volatilities. The unreported estimation results show the rolling EGARCH(1,1) volatility has weak explanatory power in explaining the sovereign CDS spread changes. We further vary the length of input and output in the rolling EGARCH(1,1) model. To be precise, we extend the range of the daily input(j)'s length and output(i)'s length to two sets: $j \in$[three-year, five-year, seven-year, ten-year] and $i \in$[one-month, three-month, six-month, one-year]. They produce similar regression results, although the EGARCH(1,1) volatility with a shorter input and output length is more

Table 2.2 – Summary Statistics

	CDS(bps)	Country(%)	Market(%)	EVZ(%)	Forex	High(%)	Slope(%)	ΔLoc_Stock(%)	ΔLoc_Fin(%)
	Mean								
France	83.00	20.38	21.40	10.92	1.32	1.61	1.49	0.04	0.05
Germany	41.02	19.86	*	*	*	*	*	0.06	0.03
Austria	71.06	22.50	*	*	*	*	*	0.01	0.02
Netherlands	50.06	17.90	*	*	*	*	*	0.04	0.07
Belgium	109.65	17.38	*	*	*	*	*	0.04	0.05
Italy	220.58	25.49	*	*	*	*	*	0.02	0.02
Spain	225.64	30.42	*	*	*	*	*	0.02	0.01
Greece	2819.75	47.81	*	*	*	*	*	-0.08	-0.16
	Standard Deviation								
France	53.23	6.19	6.52	3.04	0.09	0.36	0.42	1.32	2.01
Germany	25.02	6.15	*	*	*	*	*	1.28	1.59
Austria	49.31	5.96	*	*	*	*	*	1.37	2.01
Netherlands	28.44	5.75	*	*	*	*	*	1.12	2.38
Belgium	82.57	4.83	*	*	*	*	*	1.15	1.89
Italy	130.60	6.67	*	*	*	*	*	1.63	2.31
Spain	136.53	10.27	*	*	*	*	*	1.51	2.04
Greece	4000.56	12.99	*	*	*	*	*	2.64	4.13

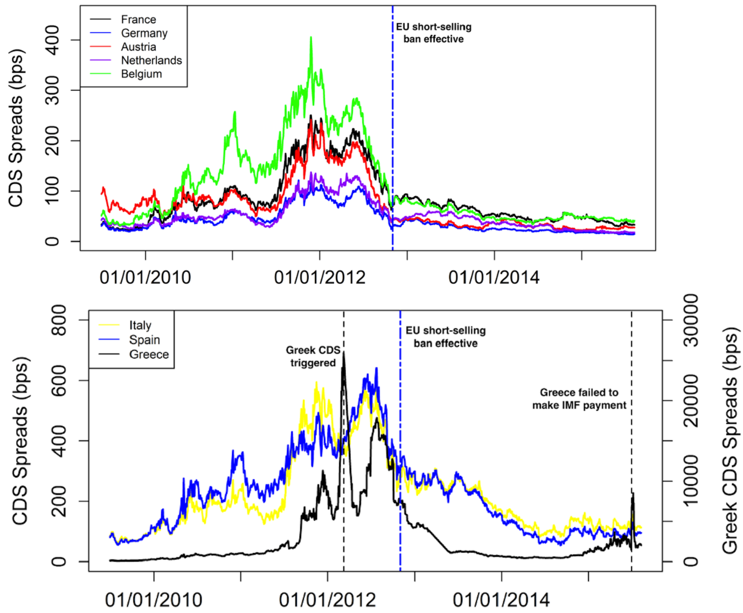
This table shows the summary statistics for our data. The data are sampled in daily frequency. The sample period is from July 01, 2009 to August 10, 2015. CDS is the five-year daily sovereign CDS spreads (basis points) collected from CMA. Country stands for the 30-day at-the-money put option-implied volatility. The underlying premier stock market index of each country's option is listed in Table 2.1 Panel A. Market stands for the market option-implied volatility, which is the EuroStoxx 50 30-day at-the-money put option-implied volatility. EVZ is the "Euro VIX," which measures the market's expectation of 30-day volatility of the USD/EUR exchange rate. Forex is the exchange rate expressed as units of U.S. dollar per euro. High refers to the U.S. corporate high-yield spread calculated as the yield spread between S&P 500 BB corporate bond yield and S&P 500 BBB corporate bond yield. Slope is the difference between the ten-year German bond yield and the two-year yield. ΔLoc_Stock refers to each country's national equity index returns. ΔLoc_Fin is the local financial index returns. For each country, * stands for the same statistics as shown in France because the corresponding variables are either regional or global variables.

volatility using the daily high, low, open, and close prices of its premier stock market index. See Table 2.1 Panel A for the detailed description of each country's premier stock market index used in our analysis. We also include the EuroStoxx 50 30-day at-the-money put option-implied volatility and the Garman and Klass (1980) historical volatility of the EuroStoxx 50 to measure the state of the European economy.

We include financial index returns and local stock market index returns as two additional local economic variables besides the country-specific volatility measures. The performance of local financial sector is measured by the local financial index returns. However, the returns of financial assets are high correlated (Blommestein et al., 2016). To create a variable that measures the performance of local financial firms

volatile than the one using a longer length. Overall, both measures perform poorly in explaining the CDS spread changes and we do not use them in this paper. The results can be provided upon request.

Figure 2.1 – Western European Sovereign CDS Spreads



This figure shows the daily five-year sovereign CDS spreads of France, Germany, Austria, the Netherlands, and Belgium (upper) and Italy, Spain, and Greece (lower). The time series spans from July 01, 2009 to August 10, 2015. The blue vertical dotted line represents the implementation date of the 2012 EU short-selling ban. The two black vertical dotted lines represent the two major Greek events' dates. Greece contains missing CDS data from Match to April 2012 and from March to May 2013. We plot them using linear interpolated CDS spreads for illustrative purposes.

independently of the performances of the local stock market and global financial market, we construct the orthogonalized local financial returns by following the orthogonalization method introduced in Dieckmann and Plank (2012). The stock market index captures the information of the underlying domestic economy, and the relationship between local stock market returns and sovereign CDS spread changes is negative (Dieckmann and Plank, 2012; Eyssell et al., 2013; Longstaff et al., 2011). Again, we use orthogonalized local stock market index returns because the local stock market index returns and European stock market index returns are highly correlated to each other. In this way, we construct a variable that represents the state of local economy independent of the European economy. See Section 2.2.4 for the detailed description of the orthogonalization method used to construct the above orthogonalized series.

We include forex, exchange rate uncertainty, and slope of yield curve as three additional regional economic variables besides market volatility. Forex is the exchange rate expressed as units of U.S. dollar per euro. Longstaff et al. (2011) and Dieckmann and Plank (2012) show that the exchange rate is an important factor in explaining variation in sovereign CDS spreads. A negative coefficient indicates the sovereign CDS spread decreases when the euro grows stronger. Exchange rate uncertainty is captured by the "Euro VIX" (EVZ), which applies VIX methodology to measure the market's expectation of the 30-day volatility of the USD/EUR exchange rate. Fontana and Scheicher (2016) suggest that the exchange rate uncertainty (EVZ) should have a positive effect on the CDS spreads because protection becomes more costly when the future path of the exchange rate is more uncertain. Collin-Dufresne et al. (2001) suggest the difference between ten-year and two-year Benchmark Treasury yields provides an indication for overall economic health as well as the expectations of future short rates. We use the difference between German ten-year government bond yield and two-year yield as the proxy for the slope of yield curve[16], following Collin-Dufresne et al. (2001). A decrease in the slope implies a weakening economy, which increases the credit spread. Following Longstaff et al. (2011), we also include the U.S. high-yield spread as a global economic variable. It is calculated as the yield spread between S&P 500 BB corporate bond yield and S&P 500 BBB corporate bond yield[17].

We do not consider Macroeconomic factors in this paper. The reason is that we perform our regression analysis based on a sample of daily frequency, while macroe-

[16]We also use ten-year Euro swap minus the three-month Euribor as the alternative proxy for the slope of the yield curve following Fontana and Scheicher (2016). It yields similar results as ours.

[17]Dieckmann and Plank (2012) suggest Bloomberg provides a yield spread between BB- and BBB-rated European corporates. However, we fail to find the same series from Bloomberg. Moreover, we do not include the U.S. investment grade yield, which is measured as the yield spread between BBB- and AAA-rated U.S. corporate bond yields as an additional variable. The reasons are the following: first, it is a less important factor compared with the high-yield spread (Longstaff et al., 2011). Second, the coefficient's sign is confusing. Longstaff et al. (2011) find U.S. investment grade yield is an important factor in explaining seven out of 26 sovereign CDS spread changes. The sign is positive in three out of seven cases and negative for the remaining four cases.

conomic variables are typically reported in monthly or quarterly frequency[18]. Using linear or spline interpolation to obtain these variables in daily frequency creates bias and might lead to a questionable regression result. For instance, Eyssell et al. (2013) use debt-over-GDP as one of the determinants to study the daily China sovereign CDS spread changes and find the coefficient is negative at the 1% significance level. We also do not include European stock market returns to avoid the multicollinearity problem in regression analysis. To be precise, European stock market returns are highly correlated to the change in European market volatility. Our preliminary investigation shows that the Pearson's pairwise correlation coefficient of EuroStoxx 50 returns and the percentage change in EuroStoxx 50 30-day at-the-money put option-implied volatility is around 0.71 in absolute value for the full sample period. In the current paper, we choose market volatility instead of EuroStoxx 50 returns to represent the state of the European economy. Please see Table 2.1 Panel B for a detailed description about local, regional, and global variables.

Table 2.2 shows the summary statistics for our data. The daily average German sovereign CDS spreads is at 41.02 bps, which is the lowest among all eight countries. The mean sovereign CDS spreads of distressed economies are high. For instance, the average sovereign CDS spreads for Italy, Spain, and Greece are all above 200 bps. In fact, the average Greek sovereign CDS spreads is at 2819.75 bps. This is not surprising because the Greek economy is the most distressed one in our sample. The distressed Greek economy can also be observed from the slope of Greek CDS spreads. Figure A2.1 in the Appendix shows the term structure of Greek CDS was completely inverted from 2010 to 2012, which suggests its local economy was in a deep crisis. Greece has the highest average country-specific option-implied volatility as 47.81%, which is more than twice the level of average market option-implied volatility (21.40%). The average country-specific volatilities of Italy and Spain are lower than Greece, but both are higher than the average market option-implied volatility. The average local stock returns and local financial returns are all positive, save for Greece. This implies Greece's local economy was still under pressure when compared with the other Western European countries in our sample.

[18]For instance, ECB Statistical Data Warehouse provides data for each European country's general government debt in monthly frequency and gross domestic product (GDP) in quarterly frequency.

2.2.3 Principal Component Analysis

The sovereign CDS spreads strongly co-move during the crisis period (Dieckmann and Plank, 2012). This is also shown in Figure 2.1, especially for those non-GIIPS countries. To investigate the degree of commonality, we perform a principal component analysis of the daily changes in the logarithm of sovereign CDS rates[19]. Table 2.3 Panel A displays the cumulative percentage of the explained variation in daily changes in the logarithm of sovereign CDS rates by the first three principal components (PCs). Western European sovereign CDS spreads have a stronger cross-sectional correlation during the European sovereign debt crisis period. To be precise, the first principal component alone can explain 80.14% of the variation, and the first three principal components can explain 90.71% of the variation. There is a clear decrease in the degree of commonality during the short-selling ban period. The first principal component alone can only explain 51.46% of the variation, and the first three PCs can explain 82.56% of the variation. One potential explanation for the decrease in commonality is that the short-selling ban may have enhanced the relationship between sovereign CDS spreads and country-specific variables while weakening the relationship between sovereign CDS spreads and regional or global variables. However, our regression results in Table 2.5 show the opposite results. The explanatory powers of country-specific volatility and local stock market returns are all muted rather than enhanced during the short-selling ban period. This suggests the short-selling ban in the sovereign CDS market might have a similar effect as the ban on short selling in equity markets, such as reducing market liquidity and hindering price discovery[20] (Beber and Pagano, 2013).

To investigate the common factors that drive this commonality, we regress the first principal component on the regional and global factors defined in Table 2.1. The regression is performed using either the market option-implied volatility or market Garman and Klass (1980) historical volatility. The estimation results are shown

[19]We include the five-year sovereign CDS of France, Germany, Austria, the Netherlands, Belgium, Italy, and Spain in our principal component analysis. We exclude the Greek sovereign CDS in the sample because it contains missing data in 2012 and 2013.

[20]We show the table of net notional amount outstanding of the European sovereign CDS market from 2009 to 2015 in the Appendix. There is a clear decrease in the amount of net notional outstanding after 2012 (implementation of the permanent EU short-selling ban). This suggests a decline in the market liquidity after the short-selling ban.

Table 2.3 – Principal Component Analysis

Panel A: PCA		
PC	EU Sovereign Debt Crisis	Short-Selling Ban
1	80.14%	51.46%
2	87.47%	72.94%
3	90.71%	82.56%

Panel B: Regression of PC1 on Regional and Global Variables				
	EU Sovereign Debt Crisis		Short-Selling Ban	
	Option	GK	Option	GK
ΔMarket	0.41** (0.06)	0.02** (0.00)	0.33** (0.03)	0.01* (0.00)
ΔForex	−4.50** (0.54)	−5.62** (0.58)	−0.42 (0.50)	−0.29 (0.58)
ΔEVZ	0.46** (0.09)	0.35** (0.09)	0.08 (0.06)	0.08 (0.07)
ΔHigh	0.50** (0.11)	0.74** (0.12)	0.34** (0.11)	0.55** (0.13)
ΔSlope	−0.55** (0.13)	−0.62** (0.13)	−0.23** (0..07)	−0.28** (0.08)
Intercept	0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)
Obs	793	793	653	653
R^2	0.34	0.29	0.23	0.12

This table displays the results of the principal component analysis of daily changes in the logarithm of sovereign CDS rates. Panel A shows the cumulative percentage of the explained variation by the first three principal components. Panel B shows the estimation results obtained by regressing the first principal component on the regional and global factors defined in Table 2.1 Panel B. EU sovereign debt crisis runs from July 01, 2009 to October 31, 2012. Short-selling ban period runs from November 01, 2012 to August 10, 2015. Option indicates the market volatility used in the regression is the 30-day at-the-money put option-implied volatility. GK indicates the market volatility used in the regression is the Garman and Klass (1980) historical volatility. We exclude Greek sovereign CDS in the sample because it contains missing data in 2012 and 2013. The robust standard errors are reported in parentheses. Significance levels at the 1% and 5% are denoted by ** and *, respectively.

in Table 2.3 Panel B. We find the estimated coefficients on market volatility are statistically significant in both periods. To be specific, the estimated coefficient on market option-implied volatility is statistically significant at the 1% level in both sub-periods, whereas the estimated coefficient on market Garman and Klass (1980) historical volatility is statistically significant at the 1% level in the crisis period and statistically significant at the 5% level in the short-selling ban period. The results indicate a few interest points. First, market volatility is a meaningful factor underlying the CDS commonality and our later results of country-by-country time series regression should show that the change in market volatility is an important factor in explaining the sovereign CDS spread changes. Second, market option-implied volatility outperforms historical volatility. Turning to the explanatory power of other regional and global variables, we find the exchange rate, exchange rate uncertainty, U.S. corporate high-yield spread, and the slope of yield curve are all important factors in explaining the sovereign CDS spread changes during the crisis period. The explanatory power of the exchange rate and exchange rate uncertainty both diminished in the short-selling ban period. The less explanatory power of the covariates and the declined R^2 values suggest that sovereign CDS spreads have weaker cross-sectional correlation during the short-selling ban period than during the EU sovereign debt crisis period. This is consistent with the PCA results shown in Table 2.3 Panel A.

2.2.4 Orthogonalization

The change in country-specific volatility and the change in market-level volatility are highly correlated to each other. This means including both of them into the regression can cause a multicollinearity problem (Blommestein et al., 2016). We solve this problem by following the method used in Blommestein et al. (2016) and Dieckmann and Plank (2012) to construct the orthogonalized change in country-specific volatility. To be precise, we obtain the orthogonalized change in country-specific volatility by regressing the percentage change in the country-specific volatility on the percentage change in the market volatility. The sum of the intercept and residuals is used to construct this orthogonalized series. In this way, we create a variable that measures the change in the state of the domestic economy independent of the European market economy. We apply the same method for local financial index returns following Dieckmann and Plank (2012) because the returns of financial assets are highly correlated (Blommestein et al., 2016). The orthogonalized local financial index returns are constructed as the intercept and residuals from a regression on world financial index returns and domestic stock market returns[21]. Fontana and Scheicher (2016) suggest orthogonalized local stock market returns improve identification. The orthogonalized local stock market returns are also adopted in Blommestein et al. (2016). Therefore, we use the orthogonalized local equity index returns in our paper. The orthogonalized local equity index returns are calculated as the intercept and residuals from a regression on EuroStoxx 50 returns. We also use the orthogonalized exchange rate uncertainty "Euro VIX" to separate the uncertainty embedded in the foreign exchange market from the uncertainty embedded in the stock market. This is

[21]We follow the exact calculation method of Dieckmann and Plank (2012). The domestic stock market returns are the original return series, and the world financial index returns are measured as the intercept and residuals from a regression on EuroStoxx 50 returns.

calculated as the intercept and residuals from a regression of the percentage change in "Euro VIX" on the percentage change in EuroStoxx 50 30-day at-the-money put option-implied volatility.

2.2.5 Sample Period Classification

Our full sample period is from July 01, 2009 to August 10, 2015. There are two reasons for using July 01, 2009 as the start date for the sample period. First, the National Bureau of Economic Research (NBER) recession data suggest the recent business recession cycle ends in June 2009. By using July 01, 2009 as the start date, our sample period does not overlap with the financial crisis. Second, the CDS "Small Bang" was implemented on June 20, 2009, which standardized CDS trading by changing the quoting conventions and coupons on Western European sovereign CDS. Oh and Patton (2016) show that the CDS "Big Bang" changed the dynamics of U.S. corporate CDS time series. By choosing the start of our sample period as July 01, 2009, we can avoid the potential structural break caused by the similar regulatory changes, namely the CDS "Small Bang," for our Western European sovereign CDS time series. Here, the CDS "Small Bang" and "Big Bang" were both used to push for standardizing trades of corporate CDS and sovereign CDS. The difference is that the CDS "Small Bang" was implemented in the EU market, while the CDS "Big Bang" was implemented in the U.S. market.

The full sample period is separated into two sub-periods using the implementation date of the 2012 EU short-selling ban. The 2012 permanent EU short-selling ban came into force on November 01, 2012. It involves 30 sovereigns and applies to all market participants, including transactions concluded outside the EEA. According to this new regulation, market participants who want to purchase CDS protection referencing EEA sovereign debt must hold those issuers' debt or have exposures "meaningfully" correlated[22] with the relevant sovereign debt (International Monetary Fund, 2013). We separate the full sample period into the following two sub-periods: first, the European sovereign debt crisis period goes from July 01, 2009 to October

[22]To meet the correlation criteria, the exposure must relate to an entity in the same referenced country. The related qualitative test of the correlation is corr>0.7, where corr stands for the Pearson's correlation coefficient between the exposure's value and sovereign debt. The amount of CDS should be proportional to the exposure's delta adjusted size.

31, 2012. Second, the short-selling ban period goes from November 01, 2012 to August 10, 2015. Figure 2.1 displays the daily five-year sovereign CDS spreads from July 01, 2009 to August 10, 2015. We use a blue vertical dotted line to identify the 2012 permanent EU short-selling ban. The plot of non-GIIPS countries shows a clear difference in CDS spread levels after the implementation of the short-selling ban. For instance, the average CDS spreads of France was 105.42 bps before the ban and 56.02 bps after the ban.

2.2.6 Greek Events

Two major Greek events that occurred during our sample period. Both of them are identified by the two black vertical dotted lines in Figure 2.1. The first event was the triggered Greek CDS payment, which happened during the European sovereign debt crisis period. This event was declared by the ISDA on March 09, 2012. The Greek CDS data stopped rolling the next business day. This ISDA announcement was followed by the Greek CDS auction. The second event was that Greece missed its International Monetary Fund (IMF) payment on June 30, 2015, which happened during the EU permanent short-selling ban period. The five-year Greek sovereign CDS spread jumped to 6739.21 bps on that day, while the average spread was at 1912.68 bps the week before the event. The five-year Greek sovereign CDS spread decreased back to 2068.87 bps on July 16, 2015 after the Greek parliament approved the austerity measure.

Our results for the Greek CDS are not affected by the two Greek events in 2012 and 2015. The reasoning for this as follows: first, there are no avaliable Greek CDS data around the first event and no avaliable option-implied volatility data around the second event. Therefore, our study for testing the explanatory power of option-implied volatility for Greek CDS are not affected by these two events because our Greek sample excludes them by nature. To be specific, CMA stopped updating Greek CDS data right after March 09, 2012. The CDS data are not avaliable until April 11, 2012[23]. Turning to the second event, the option data stopped rolling starting on June 26, 2015. It started to update again on August 03, 2015 when the

[23]In Figure 2.1, we plot those missing data using linear interpolated CDS spreads for illustrative purposes. We do not have them in our regression analysis.

Greek Stock Exchange reopened. When CDS and option-implied volatility data were reloaded, they were typically at lower levels. For instance, the five-year Greek CDS data was reloaded at 7983.96 bps on April 11, 2012. It was lower than the average five-year Greek CDS spreads (14633.30 bps) the week before the first event. The option-implied volatility data were reloaded at 64.28%, which was also lower than the average option-implied volatility (79.15%) the week before the second event. Therefore, we believe the impacts of those events on CDS or option-implied volatility diminished or died out once the data were reloaded. Our reasonings for the unaffected results of the Garman and Klass (1980) historical volatility are similar. First, there are no avaliable Greek CDS data around the first event. Second, the Greek Stock Exchange closed during the second event. Therefore, we do not have daily high, low, open, and close stock prices to calculate the Garman and Klass (1980) historical volatility [24]. Therefore, our study on testing the explanatory power of the Garman and Klass (1980) historical volatility for Greek CDS are not affected by both events because our Greek sample excludes them by nature.

Second, our results hold after deleting more data around those two events. To be precise, Greek CDS data and country-level volatility data are typically not avaliable after the events. For instance, the Greek CDS data stopped rolling the day after the first event and started to update again one month later. The country-level volatility data are not avaliable one day before the second event and reloaded after 25 working days. To ensure the effects of both events are fully removed, we manually delete the data for five working days before those two events[25] and re-estimate the model for Greek CDS. The unreported results show similar outputs as in Table 2.4 and Table 2.5. Turning to the possible impact of Greek credit events on the results of other sovereign CDSs, we believe they are not affected by those two Greek events for the following two reasons: first, Figure 2.1 has shown there is no dramatic increase in the other countries' sovereign CDS spreads around the dates of those two Greek events. Second, for each country, we re-estimate our models by manually deleting the data for five working days before the event (including event date) and five working days

[24]The last avaliable prices are reported in June 26, 2015, and the prices were reloaded again on August 03, 2015. This gives the same sample period as the option-implied volatility data.

[25]We manually delete the data for five working days before the first event (including event date). For the second event, we delete the five working days data before June 29, 2015. The second event date June 30, 2015 as well as June 29, 2015 has already been excluded in the Greek sample because of missing data.

after. The unreported regression results show similar outputs as in Table 2.4 and Table 2.5. Therefore, we conclude that our overall regression results are not affected by the 2012 and 2015 Greek events.

2.3 Model

We perform a time series analysis to study the determinants of Western European sovereign CDS spread changes. A time series analysis allows us to test factors, such as regional factors, beyond the country-specific variables. This is important for our study because one of our major volatility measures is European market volatility. Our analysis uses changes in the natural logarithm of sovereign CDS rates. We make this choice to reduce the impact of outliers. First, we test whether country-specific volatility and market-level volatility have explanatory powers for sovereign CDS spreads. For each country i in our sample, we estimate the following baseline time series regression:

$$\Delta Log(CDS)_{it} = \alpha_i + \delta_i \Delta Country_{it} + \gamma_i \Delta Market_t + \varepsilon_{it} \tag{2.1}$$

where ΔLog(CDS)$_{it}$ stands for the daily changes in the logarithm of country i's sovereign CDS rates. ΔCountry$_{it}$ is the orthogonalized change in country-specific option-implied or historical volatility. ΔMarket$_t$ is the change in market option-implied or historical volatility. To be precise, option-implied volatility is the 30-day at-the-money put option-implied volatility. Historical volatility is the Garman and Klass (1980) historical volatility.

We further include additional local, regional, and global variables in the regression. Our goal is two-fold: first, we want to test whether the explanatory powers of country-specific volatility and market volatility remain after controlling for other determinants. This allows us to test whether country-level and market-level volatilities provide additional explanatory power for sovereign CDS spreads. Furthermore, we are also interested in testing the explanatory powers of those additional variables. For each country i in our sample, we estimate the following model:

$$\Delta Log(CDS)_{it} = \alpha_i + \delta_i \Delta Country_{it} + \gamma_i \Delta Market_t + \Delta X_{it}^T \beta_i + \Delta X_t^T \eta_i + \varepsilon_{it} \tag{2.2}$$

where vector ΔX_{it} includes the orthogonalized local stock market returns and orthogonalized local financial market returns. These variables reflect the state of the local economy and the performance of local financial firms. Vector ΔX_t includes the percentage changes in forex, slope of yield curve, U.S. high-yield spread, and the orthogonalized change in "Euro VIX." These variables reflect the state of the European economy and the state of the global economy. Forex is the exchange rate expressed as units of U.S. dollar per euro. The slope of yield curve is the difference between the ten-year and two-year Benchmark Treasury yields. The U.S. high-yield spread is the yield spread between S&P 500 BB corporate bond yield and S&P 500 BBB corporate bond yield. "Euro VIX" is the EVZ index, which measures exchange rate uncertainty by applying VIX methodology to measure the market's expectation of 30-day volatility of the USD/EUR exchange rate. The orthogonalized "Euro VIX" series separates the uncertainty embedded in foreign exchange market from the uncertainty embedded in local stock market. For a more detailed description on the orthogonalization method and the definition of country-specific, regional, and global variables, please see Section 2.2.2 and Section 2.2.4.

2.4 Results

Table 2.4 Panel A shows the estimation results[26] of eight individual baseline regressions for the European sovereign debt crisis period. The model is specified in eq(2.1). There are several conclusions we can draw from the results. First, the change in market volatility is an important factor in explaining the sovereign CDS spread changes for all eight countries. It confirms our previous results from the principal component analysis that market volatility has a strong explanatory power. Both the changes in the market implied volatility and market historical volatility are statistically significant at the 1% level. However, the factor loadings on the market

[26]Our estimation results hold for both robust standard errors and Newey-West standard errors.

Table 2.4 – Determinants of Western European Sovereign CDS Spread Changes during the European Sovereign Debt Crisis Period

Panel A: Country-specific Volatility and Market Volatility

	France		Germany		Austria		Netherlands		Belgium		Italy		Spain		Greece	
Δ Log(CDS)	Option	GK	Option	GK	Option	GK	Option	GK	Option	GK	Option	GK	Option	GK	Option	GK
ΔCountry	0.04	0.00	0.12*	0.00	0.06**	0.01**	0.12**	0.00	0.04*	0.01	0.24**	0.02**	0.29**	0.01	0.10**	−0.00
	(0.07)	(0.01)	(0.05)	(0.00)	(0.01)	(0.00)	(0.04)	(0.00)	(0.02)	(0.00)	(0.04)	(0.00)	(0.04)	(0.00)	(0.03)	(0.00)
ΔMarket	0.24**	0.01**	0.20**	0.01**	0.24**	0.01**	0.21**	0.01**	0.23**	0.01**	0.30**	0.01**	0.26**	0.01**	0.17**	0.01**
	(0.03)	(0.00)	(0.03)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)	(0.04)	(0.00)	(0.04)	(0.00)	(0.04)	(0.00)
Intercept	0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	0.00	−0.00	0.00	−0.00	0.00*	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Obs	793	793	793	793	793	793	793	793	793	793	793	793	793	793	753	753
R^2	0.14	0.03	0.11	0.02	0.17	0.03	0.13	0.02	0.12	0.02	0.23	0.05	0.23	0.02	0.05	0.01

Panel B: With Domestic, Regional, and Global Variables

	France		Germany		Austria		Netherlands		Belgium		Italy		Spain		Greece	
Δ Log(CDS)	Option	GK	Option	GK	Option	GK	Option	GK	Option	GK	Option	GK	Option	GK	Option	GK
ΔCountry	0.04	0.00	0.12*	0.00	0.03*	0.01*	0.08*	0.00	0.01	0.01	0.09**	0.02**	0.18**	0.00	0.09**	−0.00
	(0.06)	(0.00)	(0.05)	(0.00)	(0.01)	(0.00)	(0.04)	(0.00)	(0.02)	(0.00)	(0.03)	(0.00)	(0.04)	(0.00)	(0.03)	(0.00)
ΔMarket	0.15**	0.01**	0.14**	0.01**	0.16**	0.01**	0.13**	0.01**	0.14**	0.01*	0.22**	0.01**	0.20**	0.01**	0.14**	0.01*
	(0.03)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)	(0.03)	(0.00)	(0.03)	(0.00)	(0.04)	(0.00)
ΔLoc_Stock	0.35	0.17	0.40	0.21	−0.20	−0.17	−0.04	−0.25	−0.74*	−0.84**	−0.73**	−0.82**	−1.21**	−1.29**	−0.38**	−0.38**
	(0.56)	(0.56)	(0.40)	(0.40)	(0.15)	(0.15)	(0.30)	(0.30)	(0.31)	(0.31)	(0.28)	(0.27)	(0.27)	(0.30)	(0.14)	(0.14)
ΔForex	−1.49**	−1.91**	−1.26**	−1.63**	−1.70**	−2.16**	−1.43**	−1.81**	−1.63**	−2.04**	−1.68**	−2.41**	−1.28**	−1.93**	−1.17**	−1.55**
	(0.22)	(0.22)	(0.22)	(0.23)	(0.23)	(0.23)	(0.20)	(0.21)	(0.22)	(0.22)	(0.24)	(0.28)	(0.26)	(0.26)	(0.36)	(0.37)
ΔEVZ	0.11**	0.07	0.19**	0.17**	0.11**	0.08*	0.14**	0.11**	0.14**	0.10*	0.17**	0.14**	0.12*	0.13**	0.17*	0.14*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.07)	(0.07)
ΔLoc_Fin	−0.58**	−0.56**	−0.77**	−0.71**	−0.65**	−0.59**	−0.44**	−0.42**	−0.72**	−0.68**	−0.80**	−0.55**	−0.94**	−0.90**	−0.14	−0.11
	(0.14)	(0.14)	(0.20)	(0.21)	(0.17)	(0.18)	(0.10)	(0.11)	(0.18)	(0.19)	(0.21)	(0.21)	(0.29)	(0.32)	(0.19)	(0.19)
ΔHigh	0.25**	0.33**	0.20**	0.27**	0.18**	0.26**	0.19**	0.26**	0.21**	0.28**	0.19**	0.33**	0.15*	0.31**	0.03	0.10
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)	(0.08)	(0.08)
ΔSlope	−0.25**	−0.28**	−0.09	−0.13*	−0.22**	−0.26**	−0.14**	−0.18**	−0.15**	−0.18**	−0.23**	−0.29**	−0.20**	−0.28**	−0.02	−0.06
	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)	(0.10)	(0.10)
Intercept	0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	0.00	0.00	0.00	−0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Obs	793	793	793	793	793	793	793	793	793	793	793	793	793	793	753	753
R^2	0.31	0.28	0.26	0.22	0.32	0.27	0.29	0.25	0.29	0.25	0.37	0.29	0.35	0.27	0.12	0.09

This table reports the results of the country-specific time series regression for eight Western European countries during the European sovereign debt crisis period. The time series covers the period from July 01, 2009 to October 31, 2012. Data are sampled in daily frequency. The results in Panel A are given by Δ Log(CDS)$_{it}$ = $\alpha_i + \delta_i\ \Delta$ Country$_{it}$ + $\gamma_i\ \Delta$ Market$_t$+ ε_{it} (eq(2.1)). The results in Panel B are given by Δ Log(CDS)$_{it}$ = α_i+ $\delta_i\ \Delta$ Country$_{it}$ + $\gamma_i\ \Delta$ Market$_t$+Δ $X_{it}^T\beta_i$ +Δ $X_t^T\eta_i$ + ε_{it} (eq(2.2)). Country$_{it}$ refers to country-specific volatility. Market$_t$ stands for European market volatility. ΔX_{it} represents the domestic covariates, including the orthogonalized local stock market returns and orthogonalized local financial market returns. ΔX_t represents the regional and global covariates, which includes the percentage change in exchange rate, slope of yield curve, U.S. high-yield spread, and orthogonalized Euro VIX. Option indicates the country-specific volatility or market volatility used in the regression is the 30-day at-the-money put option-implied volatility. GK indicates the country-specific volatility or market volatility used in the regression is the Garman and Klass (1980) historical volatility. A detailed description of variables is shown in Table 2.1 and described in Section 2.2.2. The orthogonalization method is stated in Section 2.2.4. Robust standard errors are reported in parentheses. The significant levels at the 1% and 5% are denoted by ** and *, respectively.

Table 2.5 – Determinants of Western European Sovereign CDS Spread Changes during the Short-Selling Ban Period

Panel A: Country-specific Volatility and Market Volatility

	France		Germany		Austria		Netherlands		Belgium		Italy		Spain		Greece	
Δ Log(CDS)	Option	GK	Option	GK	Option	GK	Option	GK	Option	GK	Option	GK	Option	GK	Option	GK
ΔCountry	0.02	0.00	−0.00	0.00	0.00	0.00	−0.05	0.00	0.00	0.00	0.30**	0.00	0.10**	0.00	0.11**	0.00
	(0.04)	(0.01)	(0.05)	(0.00)	(0.02)	(0.00)	(0.04)	(0.00)	(0.01)	(0.01)	(0.04)	(0.00)	(0.03)	(0.00)	(0.04)	(0.00)
ΔMarket	0.10**	0.01**	0.08**	0.00*	0.09**	0.00	0.04*	−0.00	0.08**	0.00*	0.25**	0.01**	0.25**	0.01**	0.15**	0.01
	(0.01)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)	(0.04)	(0.00)
Intercept	0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	0.00	−0.00	−0.00	−0.00	−0.00	−0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Obs	653	653	653	653	653	653	653	653	653	653	653	653	653	653	559	559
R^2	0.07	0.03	0.03	0.02	0.04	0.01	0.01	0.00	0.06	0.01	0.31	0.02	0.20	0.02	0.06	0.01

Panel B: With Domestic, Regional, and Global Variables

	France		Germany		Austria		Netherlands		Belgium		Italy		Spain		Greece	
Δ Log(CDS)	Option	GK	Option	GK	Option	GK	Option	GK	Option	GK	Option	GK	Option	GK	Option	GK
ΔCountry	0.02	0.00	−0.00	0.00	−0.00	−0.00	−0.03	0.00	0.00	0.00	0.25**	0.00	0.06*	0.00	0.11**	0.00
	(0.04)	(0.00)	(0.05)	(0.00)	(0.02)	(0.00)	(0.04)	(0.00)	(0.01)	(0.00)	(0.03)	(0.00)	(0.03)	(0.00)	(0.03)	(0.00)
ΔMarket	0.08**	0.01**	0.06**	0.00	0.09**	0.00	0.03	−0.00	0.07**	0.00	0.22**	0.01**	0.21**	0.01*	0.13**	0.01
	(0.01)	(0.00)	(0.01)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)	(0.01)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)	(0.03)	(0.00)
ΔLoc_Stock	0.57	0.50	0.60	0.59	−0.13	−0.17	0.52	0.60	0.26	0.25	−0.71**	−1.09**	−1.04**	−1.26**	−0.50**	−0.53**
	(0.42)	(0.43)	(0.32)	(0.32)	(0.21)	(0.21)	(0.49)	(0.48)	(0.30)	(0.30)	(0.20)	(0.22)	(0.27)	(0.28)	(0.10)	(0.11)
ΔForex	0.19	0.23	−0.52	−0.49	−0.50	−0.48	−0.53	−0.50	−0.13	−0.09	0.21	0.22	0.31	−0.40	−0.02	−0.02
	(0.22)	(0.23)	(0.27)	(0.27)	(0.26)	(0.26)	(0.32)	(0.32)	(0.22)	(0.23)	(0.26)	(0.34)	(0.32)	(0.37)	(0.55)	(0.55)
ΔEVZ	0.04	0.04	−0.02	−0.02	−0.02	−0.03	0.03	0.03	0.04	0.04	0.03	0.05	0.05	0.06	0.05	0.04
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.04)	(0.04)	(0.05)	(0.06)	(0.06)
ΔLoc_Fin	−0.46*	−0.51**	−0.01	−0.04	−0.24	−0.18	−0.15	−0.20	−0.01	−0.04	−0.27	−0.07	−0.29	−0.10	0.01	0.02
	(0.18)	(0.17)	(0.23)	(0.23)	(0.18)	(0.18)	(0.15)	(0.15)	(0.13)	(0.14)	(0.22)	(0.25)	(0.26)	(0.27)	(0.11)	(0.11)
ΔHigh	0.17**	0.21**	0.16*	0.19*	0.07	0.12	−0.00	0.02	0.07	0.12*	0.17**	0.37**	0.23**	0.38**	0.07	0.13
	(0.05)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)	(0.05)	(0.06)	(0.05)	(0.05)	(0.06)	(0.08)	(0.07)	(0.08)	(0.09)	(0.09)
ΔSlope	−0.00	−0.02	−0.05	−0.06	0.01	0.00	−0.08	−0.08	−0.00	−0.01	−0.17**	−0.20**	−0.14*	−0.17**	−0.14	−0.18
	(0.03)	(0.03)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)	(0.03)	(0.03)	(0.04)	(0.05)	(0.06)	(0.06)	(0.15)	(0.15)
Intercept	−0.00	−0.00*	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Obs	653	653	653	653	653	653	653	653	653	653	653	653	653	653	559	559
R^2	0.11	0.09	0.07	0.06	0.05	0.02	0.03	0.03	0.07	0.3	0.38	0.23	0.27	0.15	0.11	0.07

This table reports the results of the country-specific time series regression for eight Western European countries during the EU short-selling ban period. The time series covers the period from November 01, 2012 to August 10, 2015. Data are sampled in daily frequency. The results in Panel A are given by Δ Log(CDS)$_{it}$ = α_i + δ_i Δ Country$_{it}$ + γ_i Δ Market$_t$+ ε_{it} (eq(2.1)). The results in Panel B are given by Δ Log(CDS)$_{it}$ = α_i+ δ_i Δ Country$_{it}$ + γ_i Δ Market$_t$+Δ $X_{it}^T\beta_i$ +Δ $X_t^T\eta_i$ + ε_{it} (eq(2.2)). Country$_{it}$ refers to country-specific volatility. Market$_t$ stands for European market volatility. ΔX_{it} represents the domestic covariates, including orthogonalized local stock market returns and orthogonalized local financial market returns. ΔX_t represents the regional and global covariates, which includes the percentage change in exchange rate, slope of yield curve, U.S. high-yield spread, and orthogonalized Euro VIX. Option indicates the country-specific volatility or market volatility used in the regression is the 30-day at-the-money put option-implied volatility. GK indicates the country-specific volatility or market volatility used in the regression is the Garman and Klass (1980) historical volatility. A detailed description of variables is shown in Table 2.1 and described in Section 2.2.2. The orthogonalization method is stated in Section 2.2.4. Robust standard errors are reported in parentheses. The significant levels at the 1% and 5% are denoted by ** and *, respectively.

historical volatility estimator are much smaller than the loadings on the market implied volatility. This means the economic significance of historical volatility estimator is rather weak. Take Germany as an example: the estimated factor loading on market option-implied volatility is 0.20. This indicates that a 10% increase in market option-implied volatility translates into a 2% increase in German sovereign CDS spread. Meanwhile, the estimated factor loading on the market Garman and Klass (1980) historical volatility is 0.01, suggesting a 10% increase in the market historical volatility is associated with a 0.1% increase in the German sovereign CDS spread. Second, the coefficient for orthogonalized change in country-specific implied volatility is statistically significant for seven out of eight countries, while the coefficient for orthogonalized change in country-specific Garman and Klass (1980) historical volatility is only statistically significant for two countries. This implies that the option market contains more information than the underlying equity market. Moreover, this option market information plays an important role in explaining the sovereign CDS spread changes. The significant explanatory power of option-implied volatility is consistent with the empirical findings of Tang and Yang (2008) and Cao et al. (2010) on corporate CDS spreads.

Table 2.4 Panel B shows the estimation results with additional local, regional, and global variables for the European sovereign debt crisis period. The model is specified in eq(2.2). The changes in the exchange rate and exchange rate uncertainty are statistically significant at the 5% level for all eight countries. This echoes our results from the principal component analysis in Table 2.3. Consistent with the findings of Longstaff et al. (2011), we find a depreciation in the euro leads to an increase in sovereign CDS spread. The result of the exchange rate uncertainty is consistent with the empirical findings of Fontana and Scheicher (2016), here suggesting an increase in the exchange rate uncertainty leads to an increase in sovereign CDS spread. The changes in the high-yield spread and the slope of yield curve are statistically significant for all countries expect Greece. This suggests Greek CDS spreads co-move less with other sovereign CDS spreads. Figure 2.1 confirms this feature of Greek CDS spreads. Consistent with the empirical findings of Longstaff et al. (2011), we find an increase in the high-yield spread increases the sovereign CDS spread. The negative sign of the slope of the yield curve's coefficient suggests that a more distressed market condition leads to an increase in sovereign credit spread.

The orthogonalized local stock market returns are statistically significant for Italy, Spain, Greece, and Belgium[27]. The negative sign of the estimated coefficient is as expected and consistent with the findings of Longstaff et al. (2011) and Eyssell et al. (2013). The orthogonalized local financial returns are statistically significant at the 1% level for almost all countries. This suggests a private-to-public risk transfer and also indicates that the local financial shock contains more information beyond the local stock market returns. The coefficients for the orthogonalized local stock market returns are statistically insignificant for most non-GIIPS countries indicate the domestic stock markets for most of the non-GIIPS countries do not reveal more information once we exclude the impact from the European stock market. For most countries, the coefficients on orthogonalized change in country-specific volatility and change in market volatility remain statistically significant at the 5% level after including additional explanatory variables. This result suggests the country-level and market-level volatilities provide additional explanatory power for sovereign CDS spreads.

Table 2.5 Panel A shows the estimation results of the country-specific baseline regressions for the short-selling ban period. The coefficients for the change in the market option-implied volatility are statistically significant for all eight countries, while the coefficients for the change in the market Garman and Klass (1980) historical volatility are statistically significant for five out of eight countries. Moreover, the coefficients for the orthogonalized change in country-specific Garman and Klass (1980) historical volatility are statistically significant for none of the eight countries, while the coefficients for the orthogonalized change in the country-specific option-implied volatility are statistically significant for Italy, Spain, and Greece. Those results echo our results from Table 2.4 Panel A that the option market contains more information than the underlying equity market. Although the coefficients for the change in the market option-implied volatility are statistically significant for all non-GIIPS countries, its economic significance is weaker during the short-selling ban period. For example, we'll look at Germany. The estimated factor loading γ_i suggests a 10% increase in market option-implied volatility translates into a 2% increase in German sovereign CDS spread during the European sovereign debt crisis

[27]Belgium is associated with a higher credit risk compared with the other non-GIIPS countries during the European sovereign debt crisis period. Figure 2.1 shows the five-year Belgium sovereign CDS spreads are higher than other four non-GIIPS countries' sovereign CDS spreads during the crisis period.

period but can only translates into a 0.8% increase in German sovereign CDS spread during the short-selling ban period. For Italy, Spain, and Greece, the factor loading on the market option-implied volatility does not change much from crisis period to short-selling ban period. Now, let's take a look at Greece. The estimate of γ_i suggest a 10% increase in the market option-implied volatility translates into a 1.7% increase in Greek sovereign CDS spread during the European sovereign debt crisis period and a 1.5% increase in Greek sovereign CDS spread during the short-selling ban period. Moreover, the coefficient for the orthogonalized change in country-specific option-implied volatility becomes statistically insignificant for all five non-GIIPS countries during the short-selling ban period. These results suggest the short-selling ban plays a more important role in reducing the explanatory power of volatility estimators on non-GIIPS countries' sovereign CDS spreads.

Table 2.5 Panel B shows the estimation results with additional local, regional, and global variables for the short-selling ban period. The coefficients for the change in exchange rate and orthogonalized change in exchange rate uncertainty are statistically insignificant for all eight countries. This echoes our results from the principal component analysis. The coefficients for the orthogonalized local stock market returns are statistically significant for Italy, Spain, and Greece. This suggests the local stock markets of those distressed countries contain more information on the state of the domestic economies. The variables' explanatory power is low for non-GIIPS countries during the short-selling ban period. Let's take France as an example. R^2 is around 0.10[28] during the short-selling ban period, while R^2 is around 0.30 during the European sovereign debt crisis period. This is a 66.67% decrease in value. The explanatory power of the variables becomes slightly lower for Italy, Spain, and Greece during the short-selling period. Let's take Italy as an example. R^2 is around 0.31 during the short-selling ban period, while R^2 is around 0.33 during the European sovereign debt crisis period. Although R^2 decreased for those distressed economies during the short-selling ban period as well, the magnitude is different. For instance, the R^2 of Spanish sovereign CDS decreased around 32.23%, while the R^2 of German sovereign CDS decreased around 66.67%. This echos our previous results on the

[28]For each country, R^2 is the average value calculated by using the R^2 values from two regression results (Option and GK). For instance, the two R^2 values for France sovereign CDS are 0.11 (option) and 0.09 (GK) during the short-selling ban period, which gives an average value of 0.10. Therefore, we say the R^2 is around 0.10 for France for the short-selling ban period.

Table 2.6 – Robustness: Sweden Sovereign CDS

Δ Log(CDS)	European Sovereign Debt Crisis		Short-Selling Ban	
	(1)	(2)	(3)	(4)
ΔCountry	0.059*	0.011	0.019	0.004
	(0.023)	(0.024)	(0.031)	(0.029)
ΔMarket	0.178**	0.121**	0.045*	0.033
	(0.023)	(0.022)	(0.022)	(0.025)
ΔLoc_Stock		0.230		0.076
		(0.145)		(0.303)
ΔForex		−0.699**		−0.168
		(0.173)		(0.286)
ΔSEK_Vol		0.250**		0.111*
		(0.044)		(0.047)
ΔLoc_Fin		0.006		0.283
		(0.214)		(0.384)
ΔHigh		0.169**		0.148*
		(0.059)		(0.073)
ΔSlope		−0.074		0.064
		(0.059)		(0.048)
Intercept	−0.002	−0.001	0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.000)
Obs	793	793	653	653
R^2	0.100	0.186	0.005	0.021

This table displays the regression results of Sweden sovereign CDS in both the European sovereign debt crisis and short-selling ban periods. The European sovereign debt crisis period is from July 01, 2009 to October 31, 2012. The short-selling ban period is from November 01, 2012 to August 10, 2015. Data are sampled in daily frequency. ΔLog(CDS) is the daily changes in the logarithm of Sweden five-year sovereign CDS rates. ΔMarket and ΔCountry stands for the change in EuroStoxx 50 30-day at-the-money put option-implied volatility and orthogonalized change in 30-day at-the-money put option-implied volatility of OMXS30, respectively. ΔLoc_Stock and ΔLoc_Fin are the orthogonalized local stock market returns and orthogonalized MSCI Financial index returns. ΔForex is the percentage changes in exchange rates. ΔSEK_Vol is the orthogonalized one-month FX implied volatility of USD/SEK. ΔHigh and ΔSlope is the percentage changes in U.S. high-yield spread and slope of yield curve. Robust standard errors are reported in parentheses. Significance levels at the 1% and 5% are denoted by ** and *, respectively.

more important role of the short-selling ban in reducing the explanatory power of variables for non-GIIPS countries.

2.5 Robustness

We use five-year Sweden sovereign CDS to perform a robustness check. Sweden is not included in the previous sample because it does not adopt the euro as its domestic currency. The average Sweden sovereign CDS spreads is 31.80 bps, which is around 9 bps lower than the average German sovereign CDS spreads. We formulate three main hypotheses for Sweden sovereign CDS based on our results of non-GIIPS countries, which relate to country-specific volatility, market-level volatility, and control variables. First, the change in market-level option-implied volatility is an important factor in explaining the Sweden sovereign CDS spread changes for both the European sovereign debt crisis period and short-selling ban period. Second, the orthogonalized change in country-specific option-implied volatility is an important factor in explaining the Sweden sovereign CDS spread changes but only during the European sovereign debt crisis period. Third, the additional local, regional, and global variables play a more important role during the European sovereign debt crisis period than in the short-selling ban period.

To test these hypotheses, we collect the daily bid and ask quotes of five-year Sweden sovereign CDS from CMA. The mid-quotes are calculated as the average of the bid and ask. The 30-day at-the-money put option-implied volatility of Sweden's premier stock market index (OMXS30) is collected from Bloomberg. We use the one-month FX implied volatility of USD/SEK as the proxy for the exchange rate uncertainty. It is collected from Bloomberg using ticker USDSEKV1m. The exchange spot rate is expressed as units of U.S. dollar per Swedish Krona and is collected from Bloomberg. The orthogonalized change in country-specific option-implied volatility is calculated by regressing the percentage change in 30-day at-the-money put option-implied volatility of OMXS30 on the percentage change in EuroStoxx 50 30-day at-the-money put option-implied volatility. The sum of the intercept and residuals is used to construct this orthogonalized variable. The exchange rate uncertainty of USD/SEK is orthogonalized using EuroStoxx 50 30-day at-the money put option-implied volatility to separate the uncertainty embedded in the foreign exchange market from the uncertainty embedded in the stock market. Data are sampled in daily frequency. The orthogonalization method and sample period classification are defined the same as described in Section 2.2.4 and Section 2.2.5.

Table 2.6 columns (1) and (3), shows the estimation results of the baseline regression as specified in eq(2.1) for the European sovereign debt crisis period and short-selling ban period. As expected, the coefficient for the change in market implied volatility is statistically significant at the 5% level in both periods. Therefore, we confirm that the change in market option-implied volatility is an important factor in explaining the Sweden sovereign CDS spread changes during the European sovereign debt crisis period and short-selling ban period (hypothesis 1). The estimated factor loading is 0.178 for the European sovereign debt crisis period. This indicates that a 10% increase in the market option-implied volatility translates into a 1.78% increase in Sweden sovereign CDS spread. Turning to the short-selling ban period, the estimated coefficient for ΔMarket is 0.045. This indicates that a 10% increase in the market option-implied volatility translates into a 0.45% increase in Sweden sovereign CDS spread. This result is consistent with our previous findings on the weaker economic significance of the market option-implied volatility during the short-selling ban period. The coefficient for ΔCountry is statistically significant at the 5% level during the European sovereign debt crisis period only. This confirms that the orthogonalized change in the country-specific option-implied volatility is an important factor in explaining the Sweden sovereign CDS spread changes but only during the European sovereign debt crisis period (hypothesis 2). We find the coefficient for ΔCountry becomes statistically insignificant after controlling for other determinants, while the coefficient for ΔMarket remains statistically significant at the 1% level. This suggests the additional explanatory power mainly comes from option-implied market volatility.

Table 2.6 columns (2) and (4), shows the estimation results with additional local, regional, and global variables for both the European sovereign debt crisis period and short-selling ban period. The coefficients for the change in exchange rate, change in high-yield spread, and orthogonalized change in exchange rate uncertainty are statistically significant at the 1% for the European sovereign debt crisis period. The coefficient for the change in exchange rate becomes insignificant for the short-selling ban period, while the coefficients for the other two variables remain statistically significant but at the 5% significant level. This confirms that the additional variables play a more important role in explaining the Sweden sovereign CDS spread changes for the European sovereign debt crisis period than the short-selling ban period (hypothesis 3). The result of a significant coefficient for the orthogonalized change in exchange rate uncertainty (ΔSEK_Vol) during the short-selling ban period is different from our pervious findings on the explanatory power of exchange rate volatility. To be specific, the results shown in Table 2.5 Panel B suggest the orthogonalized change in EVZ (30-day implied volatility of USD/EUR) has no significant explanatory power in explaining the sovereign CDS spread changes for all eight countries during the short-selling ban period. This indicates the FX implied volatility on country-specific exchange rate (USD/SEK) contains more information than the FX implied volatility on the market based exchange rate (USD/EUR) for sovereign CDS contracts.

2.6 Conclusion

In the current paper, we provide an in-depth study to test the explanatory power of country-level and market-level volatilities for sovereign CDS spreads. We use two types of volatility measures, namely the put option-implied volatility and Garman and Klass (1980) historical volatility, for our analysis. Our paper adds to the sovereign CDS literature by being the first one to use the change in implied volatility to explain the sovereign CDS spread changes. The close-to-close historical volatility is typically used in papers as a historical volatility measure. We improve this by using the Garman and Klass (1980) historical volatility, which is 7.4 times more efficient than the traditional close-to-close estimator (Garman and Klass, 1980). To show that the country-level and market-level volatilities provide additional explanatory power, we include six local, regional, and global variables to control for other determinants. To study the impact of the short-selling ban on the determinants of sovereign CDS spreads, we perform our analysis for both the European sovereign debt crisis period and short-selling ban period.

We perform the country-by-country time series regressions to test the explanatory powers of the option-implied volatility for sovereign CDS spreads. Some clear results emerge. First, country-specific and market volatilities have explanatory power for sovereign CDS spread changes. Second, both the country-level and market-level implied volatilities contain more information than historical volatilities in sovereign CDS pricing. Third, the coefficients for most of the country-specific and market option-implied volatilities remain statistically significant after including additional control variables, which suggest our country-level and market-level volatilities add additional explanatory power after controlling for other determinants. Fourth, the short-selling ban reduced the explanatory powers of sovereign CDS determinants. This impact is stronger for non-GIIPS countries. Finally, we use Sweden sovereign CDS to perform a robustness test. The estimation results confirm the important roles of country-specific and market option-implied volatilities for sovereign CDS spreads.

Our study has some implications. For academics, our results show the important roles of country-level and market-level volatilities for sovereign CDS spreads. For policymakers, we show most variables lose their explanatory powers for non-GIIPS countries' sovereign CDS spreads after the ban. This suggests a partial ban on certain contracts might be more suitable than a universal ban. For investors, our results suggest the country-specific volatility index and market volatility index are good indicators for monitoring sovereign credit risk.

Bibliography

Augustin, P., Chernov, M., Song, D., 2018. Sovereign credit risk and exchange rate: Evidence from CDS quanto spreads. *NBER Working Paper 24506*, National Bureau of Economic Research, Inc.

Augustin, P., 2018. The term structure of CDS spreads and sovereign credit risk. *Journal of Monetary Economics* 96, 53-76.

Avino, D., Cotter, J., 2014. Sovereign and bank CDS spreads: Two sides of the same coins. *Journal of International Financial Markets, Institutions & Money* 32, 72-85.

Beber, A., Pagano, M., 2013. Short-selling bans around the world: Evidence from the 2007-09 crisis. *Journal of Finance* 68 (1), 343-381.

Blommestein, H., Eijffinger, S., Qian, Z.X., 2016. Regime-dependent determinants of Euro area sovereign CDS spreads. *Journal of Financial Stability* 22, 10-21.

Cao, C., Yu, F., Zhong, Z., 2010. The information content of option-implied volatility for credit default swap valuation. *Journal of Financial Markets* 13 (3), 321-343.

Collin-Dufresne, P., Goldstein S.R., Martin, J.S., 2001. The determinants of credit spread changes. *Journal of Finance* 56 (6), 2177-2207.

Cremers, M., Driessen, J., Maenhout, P., Weinbaum, D., 2008. Individual stock-option prices and credit spreads. *Journal of Banking & Finance* 32 (12), 2706-2715.

Dieckmann, S., Plank, T., 2012. Default risk of advanced economies: An empirical analysis of credit default swaps during the financial crisis. *Review of Finance* 16 (4), 903-934.

Duffie, D., 2010. Is there a case for banning short speculation in sovereign bond markets? *Financial Stability Review* 14, 55-59.

Eyssell, T., Fung, H.G., Zhang, G., 2013. Determinants and price discovery of China sovereign credit default swaps. *China Economic Review* 24, 1-15.

Fontana, A., Scheicher, M., 2016. An analysis of euro area sovereign CDS and their relation with government bonds. *Journal of Banking & Finance* 62, 126-140.

Garman, B.M., Klass, J.M., 1980. On the estimation of security price volatilities from historical data. *Journal of Business* 53 (1), 67-78.

International Monetary Fund., 2013. A new look at the role of sovereign credit default swaps. *Global Financial Stability Report*.

Kallestrup, R., Lando, D., Murgocic, A., 2016. Financial sector linkages and the dynamics of bank and sovereign credit spreads. *Journal of Empirical Finance* 38, 374-393.

Kelly, B., Pástor, L., Veronesi, P., 2016. The price of political uncertainty: Theory and evidence from the option market. *Journal of Finance* 71 (5), 2417-2480.

Longstaff, F.A., Pan, J., Pedersen, L.H., Singleton, K.J., 2011. How sovereign is sovereign credit risk? *American Economic Journal: Macroeconomics* 3 (2), 75-103.

Meine, C., Supper, H., Weiß, G., 2016. Is tail risk priced in credit default swap premia? *Review of Finance* 20 (1), 287-336.

Merton, R.C., 1974. On the pricing of corporate debt: The risk structure of interest rate. *Journal of Finance* 29 (2), 449-470.

Oh, D.H., Patton, A.J., 2016. Time-varying systemic risk: Evidence from a dynamic copula model of CDS spreads. *Journal of Business & Economic Statistics* 36 (2), 181-195.

Parkinson, M., 1980. The extreme value method for estimating the variance of the rate of return. *Journal of Business* 53 (1), 61-65.

Pu, X.L., Zhang, J.N., 2012a. Sovereign CDS spreads, volatility, and liquidity: Evidence from 2010 German short sale ban. *Financial Review* 47, 171-197.

Pu, X.L., Zhang, J.N., 2012b. Can dual-currency sovereign CDS predict exchange rate returns? *Finance Research Letter* 9 (3), 157-166.

Tang, D., Yan, H., 2008. Liquidity and credit default swap spreads. *Working paper*, University of Hong Kong.

Wang, J., Svec, J., Peat, M., 2012. A structural approach to estimate market-assessed sovereign credit risk. *Working Paper*, University of Sydney.

Appendix

This appendix provides additional information about the net notional amount of Western European sovereign credit default swap (CDS) market and the figure of Western European sovereign CDS spreads' term structure. We show the 2009-2015 annual net notional amount outstanding of Western European sovereign CDS contracts in Table A2.1. We include all eight Western European sovereign CDS contracts used in this paper, with the exception of Greece, since it contains missing net notional amount data from 2012 to 2014. This table is used to state the potential impact of the 2012 EU permanent short-selling ban on the size of European sovereign CDS market. The slopes of the CDS term structure for our Western European CDS contracts are in shown in Figure A2.1. We use this figure to provide additional evidence of the 2012 EU short-selling ban's impact on the Western European sovereign CDS spreads from the term structure point of view.

Net Notional Amount of European Sovereign CDS Outstanding

Table A2.1 shows the annual total net notional amount outstanding for the eight Western European sovereign CDS contracts used in this paper except Greece. The Greek sovereign CDS contract is excluded because it contains missing net notional amount data from 2012 to 2014. The weekly net notional amount outstanding for each sovereign CDS contract is collected from Depository Trust & Clearing Corporation (DTCC) and denominated in billions of U.S. dollars. The annual net notional amount outstanding for each contract is calculated as the weekly average within a year. The total net notional amount outstanding is calculated as the sum of the weekly average values.

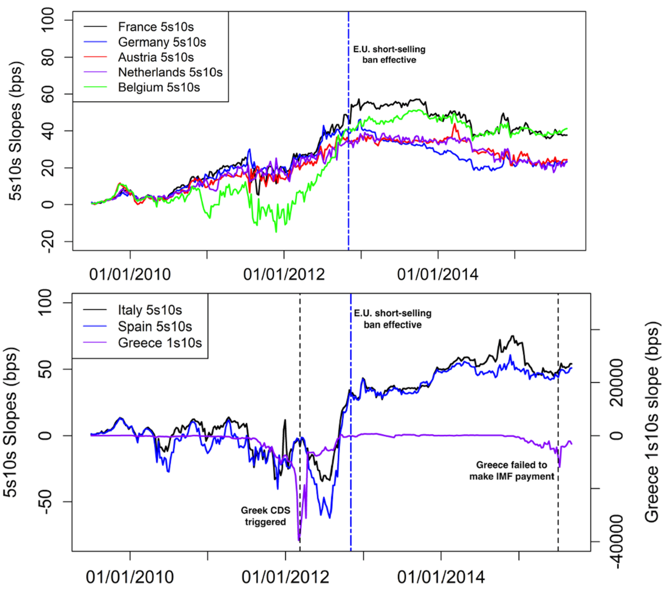
Table A2.1: Annual Net Notional Amount Outstanding ($Billion)

	2009	2010	2011	2012	2013	2014	2015
Western Europe (ex Greece)	65.9	83.2	96.4	88.9	67.9	60.7	54.2

This table reports the annual Western European sovereign CDS contracts' net notional amount outstanding. The Western European contracts include all eight Western European countries used in our paper except Greece. These countries are Austria, Belgium, France, Germany, the Netherlands, Italy, and Spain. We do not include Greek CDS, since it contains missing net notional amount data from 2012 to 2014.

There is a clear decrease in the total net notional amount of Western European sovereign CDS contracts in 2013. The annual total amount decreased from 88.9 billion USD in 2012 to 67.9 billion USD in 2013, which constitutes a decreased of nearly 23.6%. One potential reason for this drop in net notional amount might be the 2012 EU permanent short-selling ban, which was implemented on November 01, 2012; however, we cannot assert that this is the only cause. We also observe a slight decrease in the total net notional amount from 2011 to 2012. However, this fluctuation in size is small when compared to the drop in 2013.

Figure A2.1 Slopes of the CDS Term Structure



This figure shows the slopes of sovereign CDS spreads for France, Germany, Austria, the Netherlands, and Belgium (upper) and Italy, Spain, and Greece (lower). The time series spans from July 01, 2009 to August 10, 2015. The blue vertical dotted line represents the implementation date of the 2012 EU short-selling ban. The two black vertical dotted lines represent the two major Greek events' dates. Greece contains missing CDS data from Match to April 2012 and from March to May 2013. We plot them using linear interpolated CDS spreads for illustrative purposes.

Term Structure of Western European Sovereign CDS Spreads

We use the term structure of sovereign CDS spreads to reveal more information about the effects of the 2012 EU permanent short-selling ban on our Western European CDS sample. For Austria, Belgium, France, Germany, Italy, the Netherlands, and Spain, we construct the slope as the difference between ten-year and five-year sovereign CDS spreads. For Greece, we use the difference between ten-year and one-year sovereign CDS spreads to construct the slope following Augustin (2018). The reason for this is that the slope measured by the difference between ten-year and one-year spreads is negative for countries in deep crisis, whereas it remains positive for less distressed economies. Therefore, it is more appropriate to measure the slope using the difference between ten-year and one-year sovereign CDS spreads for Greece than for the rest countries.

Figure A2.1 provides additional evidence of the 2012 EU short-selling ban's impact on the sovereign CDS spreads from the term structure point of view. The 5s10s slopes of Italian and Spanish sovereign CDS spreads turned and remained positive after the implementation of the short-selling ban. Moreover, the 5s10s slope of Belgium sovereign CDS was negative before the short-selling ban and positive after the ban. The slopes of non-GIIPS countries' sovereign CDS spreads, such as France, Germany, Austria, and the Netherlands, are mostly positive during the entire sample period. However, the level of the difference between the ten-year and five-year spreads is higher in the short-selling ban period than in the European sovereign debt crisis period. For instance, the average 5s10s slope of France is 46.86 bps in short-selling ban period and 16.54 bps in European sovereign debt crisis period. A higher level of the difference between the ten-year and five-year spreads reveals a relief in domestic economic condition in the short run. One possible explanation is that the short-selling ban lowers each country's borrowing cost, which enhances the short term condition of the domestic economy. The 1s10s slope of Greek CDS experienced two major drops in value around the 2012 and 2015 Greek events. This is as expected, since the CDS slope typically inverts during an economic crisis.

3. Does the U.S. Sovereign Credit Risk Depend on Other Countries?

Author: Yi Li*

Abstract: This paper exams the dependence structure of the sovereign credit default swap (CDS) spreads between the U.S. and 36 countries located in Western Europe, Central & Eastern Europe, Latin America, and Asia. By considering different types of dynamic copulas, we find that the tail dependence coefficients of U.S.-Western European and U.S.-Central & Eastern European sovereign CDS pairs are non-zero. We perform a cross-sectional analysis to study the determinants of the tail dependence coefficients. The results show that higher trade flow and larger foreign exposure of the U.S. banking system are associated with a higher probability of large joint increases in the sovereign credit risks of the U.S. and European countries.

Keywords: U.S. Sovereign CDS; Dynamic Copulas; Tail dependence coefficient

JEL Classification: C52, G10, G15

---

*I am grateful for valuable comments and suggestions received from Angelo Ranaldo, Paul Söderlind.

3.1 Introduction

The degree of asset dependence has been well studied in other financial markets, including energy and stock markets (Reboredo, 2011; Chollete et al., 2011). However, little attention has been paid to the dependence structure of sovereign credit default swap (CDS) spreads. Thus, this paper seeks to fill the gaps in our understanding of the dependence structure of sovereign CDS spreads. Moreover, the literature on sovereign CDS often pays more attention to European sovereign CDS contracts (Dieckmann and Plank, 2012; Fontana and Scheicher, 2016; Blommestein et al., 2016) and ignores U.S. sovereign CDS. Therefore, we perform our analysis of the dependence structure with a focus on U.S. sovereign CDS spreads.

In this paper, we use the copula model to study the dependence structure of the sovereign CDS spreads between U.S. and 36 countries. We are interested in measuring the likelihood of joint extreme movements of two sovereign CDS spreads because it refers to the probability of simultaneous large changes in two countries' credit risks. For each U.S.−Country$_j$[1] sovereign CDS pair, the joint extreme movements of default probabilities is captured by the tail dependence coefficient, which can be obtained from copula model. By considering different types of copulas, we attempt to address the following two key questions in this paper: first, do U.S. sovereign CDS spreads have joint extreme movements with other countries' sovereign CDS spreads? Second, if the joint extreme movements do exist, what are the determinants of the tail dependence coefficient?

Our analysis brings new insights for academics, investors, and policymakers. For academics, we provide the first paper, to the best of our knowledge, studying the dynamic tail dependence structure of the sovereign CDS spreads between the U.S. and other countries (36 countries from four different regions). Our results provide evidence of non-zero tail dependence coefficients between U.S. and European sovereign CDS spreads. For investors, our results on the determinants of the dependence coefficient suggest that investors need to monitor the economic condition of the countries to which U.S. banks are exposed when evaluating the co-dependence of

[1]Country$_j$ with j∈[1,36], refers to each of the 36 countries we have included in this paper to study their sovereign CDS spreads' tail dependence with U.S. sovereign CDS spreads. A detailed illustration of these 36 countries can be found in Section 3.2.3.

the sovereign credit risk between the U.S. and other countries. For policymakers, the results of our cross-sectional analysis suggest that policymakers should closely watch the quality and size of the foreign exposure of the U.S. banking system as well as the risk of global trading partners to avoid the potential risk spillover.

We use a comprehensive data set of 36 countries' sovereign CDS spreads to study their dependence structures with the U.S. sovereign CDS spreads. These 36 countries include 13 Western European countries, 10 Central & Eastern European countries, 5 Latin American countries, and 8 Asian countries. We collect the 5-year sovereign CDS spreads from Credit Market Analysis (CMA), which is a widely used CDS data source (Avino and Cotter, 2014; Kallestrup et al., 2016; Meine et al., 2016). We choose December 2009 to October 2012 to perform our analysis. The reasons are the following: first, we want to focus on a period with increasing or the highest net notional amount of U.S. sovereign CDS outstanding (henceforth net notional, NN). This increasing or highest NN implies that investors pay more or most attention to the U.S. sovereign CDS contracts during this period. Second, we want to avoid the structural break introduced by the new regulations on trading standardized CDS contracts. Specifically, the new regulation of trading standardized CDS contracts of U.S., Western European, Emerging European & Latin American, and Asian sovereign CDSs went into effect in April, June, September, and December 2009, respectively. As suggested by Oh and Patton (2016), these changes in trading regulations could change the dynamics and distributional features of CDS time series, which could potentially affect our analysis. Therefore, we choose December 2009 as the start of our sample period, when all the new trading regulations had been implemented. Third, we use October 2012 as the end of our sample period to avoid the structural break introduced by the 2012 EU permanent short-selling ban, which could also affect our analysis. Based on the above reasonings, we fix our sample period from December 2009 to October 2012.

To measure the dependence structure of the sovereign CDS spreads between the U.S. and 36 countries, we include three different types of dynamic copulas: Gaussian, Student's t, and Gumbel. These copula models have different tail dependence characteristics. The Gaussian copula has zero tail dependence, while the Student's t copula has symmetric tail dependence. Meanwhile, the Gumbel copula has upper tail dependence and zero lower tail dependence. The dynamic formation of each copula follows an ARMA(1,10) process introduced in Patton (2006). The copula models are estimated using a two-stage process following Fei et al. (2017), Patton (2013), and Reboredo (2011). The best copula model is selected using the Akaike Information Criterion (AIC). The tail dependence coefficient of each 36 U.S.$-$Country$_j$ sovereign CDS pair is obtained from the best selected copula.

To study the determinants of the tail dependence coefficient, we perform a simple cross-sectional analysis with both daily and monthly frequencies. We include four explanatory variables: U.S. banks' foreign exposure, trade flow, financial dependence, and international debt-to-GDP ratio. The U.S. banks' foreign exposure is the consolidated foreign claims of the U.S. banking system on all residents, including the public sector, banks, and non-bank private sector, of another country. The trade flow refers to the trade flow from the gravity model and is constructed following the method shown in Karnaukh et al. (2015). Financial dependence is calculated as the ratio of a country's financial sector's international debt securities to the entire economy's international debt securities amount. The international debt-to-GDP ratio is calculated as the entire economy's international debt securities amount over GDP, which is used as a control variable for a country's indebtedness in our regression analysis. We use the linear interpolation to convert the quarterly variables into a monthly frequency.

With little guidance on the joint extreme movements of sovereign CDS spreads, we build our first hypothesis of the tail dependence coefficient based on the increasing NN[2]. Specifically, we find that the NN more than doubled from 2009 to 2012, as shown in Table 3.1. This feature of the increasing net CDS size is puzzling because we expect the NN to decrease after the U.S. financial crisis. An increasing net insured amount reveals that investors have increasing concerns about the U.S. sovereign credit risk, which leads them to buy more protections. We notice that this 2009 to 2012 period largely overlaps with the European sovereign debt crisis period. The worries of investors could be a possible risk spillover from Europe to the United States. Therefore, we formulate our first hypothesis as follows: if the U.S. sovereign CDS spreads do have joint extreme movements with other countries' sovereign CDS spreads, we expect this likelihood of joint extreme movements (measured by the tail

[2]NN represents the sum of net protection sold (bought) by the net sellers (buyers), which quantifies the net insured interest (Augustin et al., 2016).

dependence coefficient) to be higher between U.S. and European sovereign CDS spreads than between U.S. and Asian sovereign CDS spreads and U. S. and Latin American sovereign CDS spreads. Our second hypothesis relates to the determinants of the tail dependence coefficient. Kallestrup et al. (2016) find that the sovereign CDS spreads are significantly affected by the foreign exposures of their domestic banks. Therefore, we believe the U.S. sovereign credit risk could be affected by the foreign exposures of the U.S. banking system. If the country to which the U.S. banks are exposed is economically distressed, we believe this could have a potential impact on the health of the U.S. banking system and the U.S. sovereign credit risk. Therefore, we formulate our second hypothesis: larger foreign exposure of the U.S. banking system is associated with a higher likelihood of joint extreme movements of sovereign CDS spreads.

Our copula results show the best copula for each of the 36 U.S.$-$Country$_j$ sovereign CDS pairs is either the Student's t or Gaussian. This suggest the symmetric tail dependence for all sovereign CDS pairs. Moreover, we find that the average tail dependence coefficients of U.S.$-$European sovereign CDS pairs is higher than the average tail dependence coefficients of U.S.$-$Asian and U.S.$-$Latin American sovereign CDS pairs. In fact, the tail dependence coefficients of U.S.$-$Asian and U.S.$-$Latin American sovereign CDS pairs are almost zero. These findings of a stronger U.S.$-$European tail dependence coefficient confirms our first hypothesis. Since the tail dependence coefficients of U.S.$-$Asian and U.S.$-$Latin American sovereign CDS pairs are almost zero, we perform the cross-sectional analysis using the tail dependence coefficients of U.S.$-$European sovereign CDS pairs. The results show that higher trade flow and larger foreign exposure of the U.S. banking system are associated with a higher probability of large joint increases in the sovereign credit risks of the U.S. and European countries.

Our paper mainly contributes to the literature on studying the dependence structures of asset prices using copula models. Reboredo (2011) uses copula models to study the co-movements among crude oil prices. Patton (2006) uses copulas to study the asymmetric dependence between the Deutsche mark and the yen. Reboredo (2012) uses copulas to study the co-movements between oil price and exchange rate. Zhu et al. (2014) use copula models to study the dynamic dependence between oil and Asian stock market prices. Atil et al. (2016) use dynamic copulas to study the conditional dependence of sovereign CDS spreads. Chollete et al. (2011) use copulas to study the international diversification of national stock market indices. Fei et al. (2017) use Markov-switching bivariate copula to study the dynamic dependence between CDS spreads and equity prices. Oh and Patton (2016) use copulas to study the joint distressed probability of U.S. corporate CDS spreads. We add to this literature by studying the dynamic structure of sovereign CDS spreads' tail dependence coefficients using time-varying copulas. Moreover, by performing a cross-sectional regression analysis, we try to find the determinants of the tail dependence coefficients.

The remainder of the paper is organized as follows. Section 2 describes the sovereign CDS market and the data. Section 3 presents the copula model. Section 4 describes the cross-sectional analysis. Section 5 summarizes the results. Section 6 presents the concluding remarks.

3.2 Data Description

3.2.1 U.S. Sovereign CDS Market

A sovereign CDS contract is a derivative security that performs similarly to insurance against a future credit event of the underlying reference entity. Although a sovereign CDS contract shares many features with a corporate CDS contract, the major difference is the denominated currency. The commonly traded U.S. sovereign CDS contact is denominated in euro. The rationale behind this is to separate the sovereign risk from the contract's payment. This does not mean U.S. sovereign CDS contact cannot quote local currency. For instance, the USD−denominated U.S. sovereign CDS contract started to trade in August 2010. However, this type of contract is less liquid than the Euro−denominated one and may require a liquidity premium (Chernov et al., 2017). The U.S. sovereign CDS contract covers the following credit events: failure to pay, restructuring, and repudiation/moratorium. According to the International Swaps and Derivatives Association (ISDA), a U.S. sovereign CDS contract has a three-business-day grace period for failure to pay. Credit events covered in the U.S. sovereign CDS contract will trigger a CDS auction. A CDS auction process is authorized by ISDA and administered by both Markit and Creditex. The

Table 3.1 – U.S. Sovereign CDS Net Notional: Outstanding Amount and Percentage of Global Sovereign CDS

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Net ($Billion)	1.29	1.98	2.44	4.57	4.40	3.46	3.71	1.45	0.76	1.18	1.41
Ratio(%)	0.92%	1.37%	1.38%	2.18%	2.17%	2.03%	2.11%	0.96%	0.56%	0.93%	1.14%

This table reports the U.S. sovereign CDS net notional amount outstanding and the ratio of the U.S. sovereign CDS's net notional amount outstanding to the global sovereign CDS's net notional amount outstanding. The weekly net notional amount outstanding values are collected from Depository Trust & Clearing Corporation (DTCC) and denominated in billion USD. Data are expressed in average value and reported on a yearly basis. The net notional amount outstanding of global sovereign CDS is calculated as the sum of the net notional amount outstanding of 41 countries' sovereign CDSs. These 41 countries are the following: Austria, Belgium, Brazil, Bulgaria, China, Colombia, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Iceland, Ireland, Israel, Italy, Japan, Kazakhstan, Latvia, Lithuania, Malaysia, Mexico, the Netherlands, Norway, Korea, Panama, Peru, Philippines, Poland, Qatar, Romania, Russia, Slovak, South Africa, Spain, Sweden, Turkey, the United Kingdom, and the United States. We cannot include other sovereign CDSs in our global CDS sample due to their limited net notional amount outstanding data throughout our sample period. The weekly net notional amount outstanding for each sovereign CDS contract is collected from the Depository Trust & Clearing Corporation (DTCC) and denominated in billion U.S. dollars. Data are expressed in average value and reported on a yearly basis.

net notional amount outstanding of U.S. sovereign CDS is small. Table 3.1 shows that the annual net notional amount outstanding of U.S. sovereign CDS reached its highest level at around $4.5 billion for the 2011 to 2012 period. At the same time, the annual net notional amount outstanding of other large economies' sovereign CDS contracts, such as France and Italy, are above $20 billion[3]. Cash settlement auction has been incorporated into the standard CDS document since the 2009 CDS "Big Bang" protocol. The advantage of cash settlement over physical settlement is that it reduces the potential for heightening the underlying bond market volatility caused by "naked" CDS buyers.

3.2.2 Sample Period Classification

We study the relationships between the U.S. and 36 countries' sovereign CDS spreads from December 2009 to October 2012. Our analysis is carried out for the December 2009 to October 2012 period based on the following two reasons: first, we want to focus on the period with increasing or the highest net notional amount outstanding of U.S. sovereign CDS contracts. The net notional amount outstanding of a CDS contract reflects its market size. A period with increasing

[3]The annual net notional amount outstanding of Italian sovereign CDS and French sovereign CDS are $24.1 billion and $21.2 billion in 2011 and $20.9 billion and $21.2 billion in 2012.

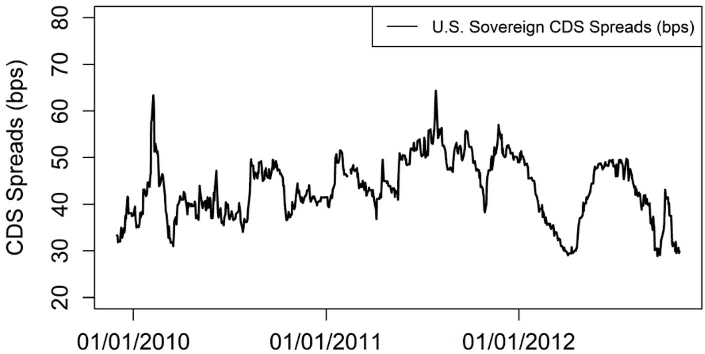
or the highest net notional amount outstanding implies investors pay more or most attention to the U.S. sovereign CDS contract during this period. Table 3.1 shows that the net notional amount outstanding of U.S. sovereign CDS was $1.29 billion in 2008 and increased to $2.44 billion at 2010. The annual net notional amount outstanding reached the highest level (around $4.5 billion) for the 2011 to 2012 period and declined afterwards. The yearly ratios (%) from 2008 to 2018 show similar features. For instance, the U.S. sovereign CDS represented around 0.92% of the global sovereign CDS market in terms of net notional amount outstanding in 2008. This ratio increased to 1.38% in 2010 and reached the highest level (around 2.17%) in the 2011 to 2012 period and declined afterwards. These features suggest we should perform our analysis based on the sample period from 2008 to 2012. However, we could not consider 2008 as the start of our sample period due to the lack of sovereign CDS data[4]. Moreover, a set of new regulations on trading standardized CDS contracts of U.S., Western European, Emerging European & Latin American, and Asian sovereign CDSs were implemented in April, June, September, and December 2009, respectively (Markit, 2009; Haworth, 2011). Moving towards standardized CDS contracts changed the dynamics and distributional features of CDS time series (Oh and Patton, 2016). This could affect our analysis. Therefore, we choose December 2009 as the start of our sample period, when all the new trading regulations had been implemented[5].

Second, we choose October 2012 as the end of our sample period to avoid the structural break introduced by the implementation of the 2012 EU permanent short-selling ban. This EU short-selling ban was implemented on November 01, 2012, which involved 30 sovereigns and applied to all market participants, including those transactions concluded outside the European Economic Area (EEA) (International Monetary Fund, 2013). We end our sample period in October 2012 before the trading of European sovereign CDS contracts entered into a new regime. Although the 2012 EU short-selling ban does not affect the Latin American and Asian sovereign CDS contracts, it still has a direct impact on the 23 European sovereign CDS contracts

[4]For instance, we cannot study the dependence structure between U.S. and Slovenia sovereign CDS spreads in 2008 because CMA started to report Slovenia CDS spreads in late 2008. This also holds for Norwegian sovereign CDS.

[5]Moreover, the National Bureau of Economic Research (NBER) recession data show that the recent business recession cycle ends in June 2009. By using December 2009 as the start of our sample period, we avoid the overlap with the financial crisis period.

Figure 3.1 – Daily five-year U.S. sovereign CDS spreads from December 2009 to October 2012



included in our sample. Therefore, it is necessary to consider the potential impact of the implementation of the 2012 EU permanent short-selling ban. Moreover, we have already stressed that we want to focus on the period with increasing or the highest U.S. sovereign CDS net notional amount outstanding, and Table 3.1 shows that the notational amount of U.S. sovereign CDS contracts declined after 2012. Therefore, by using October 2012 as the end of our sample period, we not only avoid the structural break introduced by the EU short-selling ban but also provide analysis of the most interesting/attractive period of U.S. sovereign CDS with high net notional amount outstanding.

3.2.3 The Data Set

We include 36 countries' sovereign CDS spreads to study their dependence structures with the U.S. sovereign CDS spreads. These 36 countries belong to four different regions. Specifically, we include the daily five-year mid-quotes of 13 Western European sovereign CDSs (Austria, Belgium, Denmark, France, Germany, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, and the United Kingdom), 10 Central & Eastern European sovereign CDSs (Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Lithuania, Poland, Romania, Slovakia, and Slovenia), 5 Latin American sovereign CDSs (Brazil, Colombia, Mexico, Panama, and Peru), and

8 Asian sovereign CDSs (China, Indonesia, Japan, Korea, Malaysia, Philippines, Thailand, and Vietnam). The daily five-year sovereign CDS bid and ask quotes are collected from CMA. CMA aggregates the quotes from a minimum of three distinct sell side members. It is widely used as the CDS data source (Avino and Cotter, 2014; Kallestrup et al., 2016; Meine et al., 2016). The daily mid-quote is calculated as the average value of daily bid and ask. The sample period is from December 01, 2009 to October 31, 2012.

The statistical description of daily U.S. sovereign CDS spreads together with the statistical descriptions of the other 36 countries' sovereign CDS spreads are shown in Table 3.2. The average value of U.S. sovereign CDS spreads is around 43.33 bps, which is the second smallest value among all countries. U.S. sovereign CDS spreads also have the smallest standard deviation at 6.64. The U.S. sovereign CDS spreads are slightly negatively skewed with a positive 5s10s slope. Distressed economies, such as Ireland and Portugal, have high CDS rates, which are both above 500 bps. This is consistent with the findings of Atil et al. (2016). Moreover, four countries (Ireland, Italy, Portugal, and Spain), whose economies are severely hit during the EU sovereign debt crisis, have negative 5s10s slopes. This feature of the inverted slope is commonly seen in CDS and bond spreads during a distressed period. The sovereign CDS spreads of most countries are positively skewed. Large economies typically have low CDS spreads. For example, the average values of China, Germany, U.K., and U.S. sovereign CDS spreads are all below 100bps. Other Western European countries, such as the Netherlands, Norway, and Sweden, also have comparably low CDS spreads. For instance, the average value of Sweden sovereign CDS spreads is 43.35 bps, which is similar to the average value of U.S. sovereign CDS spreads.

Figure 3.1 shows the movements of daily U.S. sovereign CDS spreads. The daily spread reached the highest value on July 28, 2011 but quickly fell back to the mean value within one month. The peak of U.S. sovereign CDS spreads in July 2011 was caused by the 2011 U.S. debt ceiling crisis. It ended on Sunday July 31, 2011, when President Obama announced the leaders of both parties had reached an agreement to lift the debt ceiling. The U.S. sovereign CDS spread fell below 55 bps the next day. Although the U.S. sovereign CDS spreads increased in the 2011 U.S. debt ceiling crisis, we do not believe this event has any significant impact on our results of the tail dependence coefficients of the 36 U.S.$-$Country$_j$ sovereign CDS pairs

Table 3.2 – Statistical Description of Sovereign CDS Spreads

	Mean	Std.Dev	50^{th} Percentile	5^{th} Percentile	95^{th} Percentile	Skewness	Kurtosis	Jarque-Bera	5s10s
Austria	107.76	47.48	87.00	56.97	194.82	0.81	2.34	0.00	14.80
Belgium	173.01	79.78	154.79	54.02	310.00	0.31	2.21	0.00	6.14
Brazil	129.25	21.28	123.91	103.64	164.66	1.01	4.02	0.00	32.17
Bulgaria	271.55	65.12	261.84	185.43	404.14	0.43	2.82	0.00	19.17
China	94.46	28.87	83.82	60.98	147.51	0.89	3.02	0.00	29.04
Colombia	130.36	23.67	126.03	100.00	171.13	0.63	2.93	0.00	29.55
Croatia	114.40	27.84	108.98	82.40	175.00	1.13	3.40	0.00	19.85
Czech	104.61	27.83	94.60	75.00	172.22	1.17	3.95	0.00	18.95
Denmark	68.21	39.49	45.63	29.82	134.02	0.66	1.76	0.00	11.00
Estonia	339.38	116.19	288.81	203.76	545.99	0.55	1.86	0.00	11.57
France	116.74	58.03	93.85	38.62	216.42	0.47	1.90	0.00	18.47
Germany	59.30	24.72	51.26	26.86	103.70	0.57	2.05	0.00	17.87
Hungary	378.22	133.20	344.50	196.59	597.13	0.45	2.02	0.00	13.59
Indonesia	169.67	33.03	163.50	129.96	225.62	1.15	4.91	0.00	51.27
Ireland	500.48	226.13	570.00	146.64	809.02	−0.17	2.12	0.00	−69.28
Italy	285.62	148.43	217.25	106.05	534.91	0.44	1.71	0.00	−3.05
Japan	150.78	25.65	147.05	119.00	200.21	0.75	3.00	0.00	30.63
Korea	113.67	26.98	106.28	77.81	161.17	0.90	3.94	0.00	27.06
Lithuania	256.80	48.81	255.26	172.26	352.36	0.18	3.24	0.00	11.19
Malaysia	101.87	26.23	94.58	72.45	147.42	1.02	3.90	0.00	29.27
Mexico	126.17	21.41	120.97	99.86	161.85	1.01	4.32	0.00	30.47
Netherlands	66.77	31.37	53.63	30.85	123.13	0.64	1.97	0.00	15.21
Norway	26.38	9.40	23.00	16.22	46.00	1.09	3.21	0.00	10.52
Panama	120.77	23.90	116.08	86.52	159.40	0.69	3.37	0.00	28.12
Peru	133.66	23.05	127.80	103.96	175.06	0.80	3.31	0.00	30.47
Philippines	156.37	27.54	151.70	124.21	201.70	0.85	4.12	0.00	45.64
Poland	169.68	54.68	149.98	96.48	280.84	0.88	2.88	0.00	24.29
Portugal	644.04	365.87	543.13	115.55	1187.90	0.20	1.73	0.00	−116.43
Romania	332.26	74.01	311.06	216.63	448.58	0.26	2.07	0.00	15.40
Slovakia	143.23	79.92	91.84	69.55	295.00	0.78	2.06	0.00	20.29
Slovenia	197.28	148.16	88.20	60.98	435.00	0.59	1.64	0.00	20.04
Spain	312.86	130.94	299.77	111.01	557.43	0.33	2.40	0.00	−10.07
Sweden	43.35	14.80	38.75	23.63	71.12	0.65	2.62	0.00	13.29
Thailand	311.83	61.92	305	233.94	414.70	0.61	2.66	0.00	29.68
U.K.	70.37	13.87	69.95	50.38	95.48	−0.02	3.09	0.50	13.71
U.S.	43.33	6.64	43.11	31.00	53.05	−0.06	2.60	0.05	14.26
Vietnam	59.30	15.62	54.72	37.11	87.12	0.49	2.45	0.00	36.83

This table provides summary statistics of daily five-year U.S. sovereign CDS spreads and the summary statistics of daily five-year sovereign CDS spreads of 36 other countries. These 36 countries belong to four different regions: Western Europe, Central & Eastern Europe, Latin America, and Asia. The Western European countries are the United Kingdom, Austria, Belgium, France, Germany, Italy, the Netherlands, Portugal, Spain, Ireland, Sweden, Norway, and Denmark. The Central & Eastern European countries are Bulgaria, Croatia, Estonia, Hungary, Poland, Slovakia, Slovenia, Lithuania, Poland, and the Czech Republic. The Latin American countries are Brazil, Colombia, Mexico, Panama, and Peru. The Asian countries are China, Indonesia, Korea, Malaysia, Philippines, Thailand, Vietnam, and Japan. The daily bid and ask quotes of five-year sovereign CDS are collected from CMA. The daily mid-quote is calculated as the average value of the daily bid and ask. Time series covers the period from December 01, 2009 to October 31, 2012. The p-value is reported for the Jarque-Bera test for the null of normality. A 5s10s slope is the slope measured as the difference between ten-year and five-year sovereign CDS spreads. The reported 5s10s stands for the average daily 5s10s slope over the entire sample period.

for the following reasons: first, we find that none of the other 36 sovereign CDS spreads co-moved with U.S. sovereign CDS spreads during the July 2011 U.S. debt ceiling crisis period. Specifically, we find that none of the other sovereign CDS spreads reached a peak value on July 28, 2011 or around the end of July 2011 and then quickly declined at the beginning of August 2011. In another word, there is no joint extreme CDS movement (tail movement) triggered by this event. In fact, Table 3.5 shows the tail dependence coefficients of most U.S.−Asian and U.S.−Latin American sovereign CDS pairs are almost zero. If the U.S. debt ceiling crisis does have a universal impact on the tail dependence, none of the CDS pairs should have a zero tail dependence coefficient. Second, we re-estimate the tail dependence coefficients using a sample period from November 2012 to December 2014, which includes the 2013 U.S. debt ceiling crisis. If the U.S. debt ceiling crisis in general does have an impact on the tail dependence structure of U.S.−Country$_j$ sovereign CDS pairs, we should expect to see a larger than zero tail dependence coefficient. We choose the five-year sovereign CDS spreads of France, the U.K., and Germany to perform our test because they all have high tail dependence with U.S. sovereign CDS spreads during the December 2009 to October 2012 period, as shown in Table 3.5. Our unreported estimation results show that all U.S.−France, U.S.−U.K., and U.S.−German sovereign CDS pairs choose Gaussian copulas. This indicates that the tail dependence coefficients for all three CDS pairs are zero. In other words, we again show that the U.S. debt ceiling crisis has no significant impact on the tail dependence coefficient.

3.3 Copula Model

3.3.1 Marginal Distribution

The daily changes in the logarithm of sovereign CDS rates, denoted as r_t, are modelled with either the ARMA(p,q)-GARCH(1,1)-skT model or ARMA(p,q)-EGARCH(1,1)-skT model. The optimal (p,q) combination with p∈[0,5] and q∈[0,5] is selected using the Bayesian information criterion following Atil et al. (2016). The EGARCH model incorporates the asymmetric volatility. $\gamma < 0$ suggests that volatility increases more in response to a negative shock than to a positive shock. We choose the EGARCH(1,1) model over the GARCH(1,1) model if the leverage coefficient γ is significant at the 5% level. The filtered standardized residuals are modelled using Hansen (1994) skewed t distribution, which has two "shape" parameters: ζ (asymmetry) and ν (degrees of freedom) with ν>2. The model collapses to the Student's t distribution when the skewness parameter ζ goes to 0. Model becomes skewed Normal distribution when ν approaches infinity. We recover the Normal distribution when ζ goes to 0 and ν approaches infinity. The generalized forms of ARMA(p,q)-GARCH(1,1)-skT and ARMA(p,q)-EGARCH(1,1)-skT models are as follows:

$$r_t = a_0 + \sum_{i=1}^{p} a_i r_{t-i} + \varepsilon_t + \sum_{j=1}^{q} b_j \varepsilon_{t-j} \tag{3.1}$$

GARCH(1,1) model

$$\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + \alpha\varepsilon_{t-1}^2 \tag{3.2}$$

EGARCH(1,1) model

$$\log(\sigma_t^2) = \omega + \beta\log(\sigma_{t-1}^2) + \alpha|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}| + \gamma(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}) \tag{3.3}$$

where a_0 and ω are constants; a_p and b_q stand for the parameters of AR lag p and MA lag q; β and α are the parameters of the GARCH and ARCH components of GARCH model. γ is the scale of asymmetric volatility. A positive γ suggests that volatility increases more in response to a positive shock than to a negative shock. The Uniform(0,1) variable is obtained through the probability integral transformation $u = F(x)$, where $F(\cdot)$ stands for the skewed Student's t cumulative distribution function.

The goodness-of-fit of the marginal distribution is evaluated using different methods. The Ljung-Box test and Engle (1982) Lagrange multiplier test are used to exam whether autocorrelation and ARCH effect remained in the residuals (Zhu et al., 2014; Reboredo, 2011). A p-value of LB(10) test higher than 0.05 indicates that the null of standardized residuals are not autocorrelated at lag 10 cannot be rejected at the 5% significant level. A p-value of the LM(10) test higher than 0.05 means the null of no ARCH effect at lag 10 cannot be rejected at the 5% significant level. Diebold et al. (1998) suggest that if the marginal distribution is correctly specified, û should be i.i.d. uniform(0,1) distributed. We perform the test in two steps: first, we use the LB(10) test[6] to exam the serial correlation of the first four moments of $(\hat{u}-\bar{u})^j$, $j \in \{1,2,3,4\}$ (Fei et al., 2017). Second, we use the Cramér-von Mises test to evaluate whether the transform is Uniform(0,1) distributed[7]. If û passes both tests, we can conclude that our marginal distribution model is not mis-specified and copula model can correctly capture the co-movement between sovereign CDS returns (Reboredo, 2011).

3.3.2 Copula Function

The dynamic Gaussian, Student's t, and Gumbel copulas are used to study the dependence structure of U.S.−Country_j CDS pairs. We also consider the dynamic Clayton and the dynamic rotated Clayton copulas in our preliminary analysis. However, the estimation results show that both models are inferior and not selected by any of the U.S.−Country_j sovereign CDS pairs. Therefore, we do not report the estimation results of these two dynamic copula models in the paper. Gaussian, Student's t, and Gumbel copulas have different tail dependence characteristics. The Gaussian copula has zero tail dependence. The Student's t copula has symmetric tail dependence, while the Gumbel copula has asymmetric tail dependence. Specifically, Gumbel copula has upper tail dependence and zero lower tail dependence. The dynamic formation of the Gaussian, Student's t, and Gumbel copulas follows Patton (2006),

[6] Patton (2006) and Reboredo (2011) use the LM statistic to examine the serial correlation of the first four moments of $(\hat{u}-\bar{u})^j$, $j \in \{1,2,3,4\}$. A p-value higher than 0.05 suggests the i.i.d. assumption cannot be rejected at the 5% level. We use this method as the alternative goodness-of-fit test, and the unreported results show that the p-values are higher than 0.05 for all series.

[7] We also employ other tests, such as Kolmogorov-Smirnov and Anderson-Darling tests, to evaluate whether the transforms are Uniform(0,1) distributed. The results of both tests confirm that we cannot reject the Uniform(0,1) assumption at the 5% significant level.

where the time-varying dependence structure follows an ARMA(1,m) process

$$\gamma_t = \Lambda(\omega + \varphi\gamma_{t-1} + \psi\Gamma_t) \tag{3.4}$$

$$where \quad \Gamma_t = \begin{cases} \frac{1}{m}\sum\limits_{j=1}^{m}\Phi^{-1}(u_{1,t-j})\Phi^{-1}(u_{2,t-j}) & Gaussian \\ \frac{1}{m}\sum\limits_{j=1}^{m}t_v^{-1}(u_{1,t-j})t_v^{-1}(u_{2,t-j}) & Student's\ t \\ \frac{1}{m}\sum\limits_{j=1}^{m}|u_{1,t-j}-u_{2,t-j}| & Gumbel \end{cases}$$

where γ is the dependence measure of interest and m is set as 10 following Patton (2006) and Fei et al. (2017). Φ^{-1} is the inverse of the standard normal distribution function, while t_v^{-1} stands for the inverse of the Student's t distribution function. For Gaussian and Student's t copulas, γ_t stands for ρ_t. For Gumbel copulas, γ_t refers to δ_t. For Gaussian and Student's t copulas, $\Lambda(y) = tanh(y/2) = (1-e^{-y})(1+e^{-y})^{-1}$ takes the modified logistic transformation to ensure $\rho_t \in (-1,1)$. For Gumbel copula, $\Lambda(y) = 1 + e^y$ to ensure $\delta_t \in (1,\infty)$. The coefficients of lower and upper tail dependence coefficients for the Gaussian copula are $\lambda^U = \lambda^L = 0$. The Student's t copula has symmetric upper and lower tail dependencies. That is λ^U=λ^L=$2t_{v+1}(-\sqrt{v+1}\sqrt{\frac{1-\rho}{1+\rho}})$, where t_{v+1} stands for the cdf of a univariate Student's t distribution with $v + 1$ degrees of freedom. For the Gumbel copula[8], the coefficient of lower tail dependence $\lambda^L = 0$ and the coefficient of the upper tail dependence is $\lambda^U = 2 - 2^{\frac{1}{\delta}}$.

3.3.3 Estimation

Copula models are estimated using a two-stage process (Fei et al., 2017; Patton, 2013; Reboredo, 2011). First, we estimate the parameters of the marginal distributions.

[8]Following Patton (2013), we define the range of δ (Gumbel parameter) as $\delta \in (1, \infty)$. Alternatively, δ can be defined as $\delta \in [1, \infty)$. When $\delta = 1$, we obtain the independence copula.

Second, we estimate the parameters of copula models conditional on the margins. The log-likelihood function is expressed as

$$\mathcal{L}(\theta_1,\theta_2,\alpha) = \sum_{t=1}^{T} lnc[F(x_t;\theta_1),G(y_t;\theta_2);\alpha]+\sum_{t=1}^{T} lnf(x_t;\theta_1)+\sum_{t=1}^{T} lng(y_t;\theta_2) \tag{3.5}$$

where θ_1,θ_2 are the parameters for the marginal distributions. The second stage ML estimation can be expressed as finding the α=arg $\underset{\alpha}{max}\sum_{t=1}^{T} lnc[\hat{u}_{1,t},\hat{u}_{2,t};\alpha]$, where $\hat{u}_{1,t} = F(x_t;\hat{\theta}_1)$ and $\hat{u}_{2,t} = G(y_t;\hat{\theta}_2)$[9]. The two-step ML estimator of copula parameters is asymptotically normal and consistent. Although it is not efficient, the simulation results from Joe (2005) and Patton (2006) show that the efficiency loss is generally small in practice. The best copula model is selected using the Akaike Information Criterion following Fei et al. (2017), Atil et al. (2016), Reboredo (2011, 2012, 2013).

3.4 Cross-Sectional Analysis

We perform a cross-section analysis to study the determinants of the tail dependence coefficient. Recall that a high tail dependence coefficient[10] implies a high probability of simultaneous large increases in the sovereign credit risks of U.S. and country$_j$. Our empirical analysis is a panel regression with time-fixed effects of the tail dependence

[9]Our log-likelihood function follows the expression from Reboredo (2011). Some papers, such as Fei et al. (2017) and Zhu et al. (2014), use a shorter expression by summarised the log-likelihood of the margins. They are essentially the same.

[10]Table 3.4 shows that the best selected copula is either the Gaussian or Student's t. This implies that the value of the tail dependence coefficient is the same for both upper and lower tails. To interpret the results of the cross-sectional analysis, we will simply use the phrase tail dependence coefficient to stand for the upper tail dependence coefficient. The reasons are as follows: first, for measuring the joint extreme movements of CDS spreads, especially the joint default probabilities (credit risk), we should use the upper tail dependence coefficient (Meine et al., 2016). Second, the upper and lower tail dependence coefficients have the same value for all 36 sovereign CDS pairs.

coefficients on explanatory variables given by the following equation:

$$\begin{aligned}\text{Tail dependence}_{it} &= \alpha + \beta_1 \text{Bank foreign exposure}_{it} + \beta_2 \text{Trade flow}_{it} + \\ &\beta_3 \text{Financial dependence}_{it} + \beta_4 \text{International debt-to-GDP}_{it} + \upsilon_t + \varepsilon_{it}\end{aligned} \tag{3.6}$$

Our choice of using a panel regression with time-fixed effects follows Augustin et al. (2016). The regression analysis is performed in both monthly and quarterly frequencies. Although all the explanatory variables are reported with a quarterly frequency, we still include the monthly regression for the following two reasons: first, we use it as a robustness test to see whether the results from a regression analysis using quarterly data are consistent with the results from a regression analysis using monthly data. Second, our dynamic tail dependence coefficient has a daily frequency. We can extract more information from the time-varying dependence coefficient by performing regressions with both monthly and quarterly frequencies. We use linear interpolation to transform the quarterly explanatory variables into monthly frequency. We report the results in Table 3.6, with standard errors clustered by country following Augustin et al. (2016). The unreported results show that our findings are robust for double clustering by country and month/quarter.

The tail dependence in eq(3.6) is the tail dependence coefficient implied by the best selected dynamic copula. The best selected dynamic copula for each U.S.$-$Country$_j$ sovereign CDS pair is shown in Table 3.4. The daily tail dependence coefficients are averaged into monthly and quarterly frequencies. We include the bank foreign exposure, trade flow, financial dependence, and international debt-to-GDP ratio as the explanatory variables[11]. The bank foreign exposure is the consolidated foreign claims of the U.S. banking system on all residents, including the public sector, banks, and non-bank private sector, of another country. This consolidated banking statistic

[11]We also construct the U.S. export and import variables as well as an alternative bank foreign exposure variable as the potential candidates for the explanatory variables. The U.S. export is the export from the United States to another country. The U.S. import is the import from another country to the United States. However, both variables are highly correlated with the trade flow. Using a univariate regression for each of these variables, we find that trade flow has the highest t-statistics. Therefore, we include trade flow in our cross-sectional analysis. The alternative bank foreign exposure factor is measured as the BIS consolidated foreign claims of the U.S. banking system on the banking sector of another country. However, this variable is not avaliable for small economies, such as Estonia, Croatia, Lithuania, Slovakia, and Slovenia. Therefore, we do not consider this variable in our analysis due to limited data.

Table 3.3 – Estimation Results of Marginal Distributions

	Mean	Variance				Skew T		Goodness-of-Fit						
	a_0	ω	β	α	γ	υ	ζ	LB(10)	LM(10)	m1	m2	m3	m4	CvM
Austria	−0.000 (0.001)	0.000* (0.000)	0.932*** (0.009)	0.067*** (0.012)	–	5.114*** (0.720)	−0.019 (0.043)	0.869	0.997	0.847	0.529	0.743	0.735	0.422
Belgium	0.000 (0.001)	−0.121** (0.048)	0.980*** (0.007)	0.116*** (0.025)	0.026** (0.013)	7.398*** (1.678)	−0.039 (0.048)	0.626	0.759	0.828	0.519	0.666	0.509	0.945
Brazil	−0.000 (0.001)	0.000*** (0.000)	0.646*** (0.060)	0.217*** (0.025)	–	7.777*** (1.829)	0.118** (0.048)	0.633	0.635	0.589	0.908	0.341	0.980	0.990
Bulgaria	−0.002 (0.003)	−0.287*** (0.064)	0.956*** (0.009)	0.276*** (0.026)	0.038*** (0.012)	3.901*** (0.336)	0.009 (0.046)	0.786	0.197	0.654	0.486	0.807	0.400	0.970
China	−0.000 (0.001)	0.000*** (0.000)	0.801*** (0.023)	0.160*** (0.023)	–	5.303*** (0.794)	0.105** (0.042)	0.732	0.804	0.812	0.647	0.773	0.346	0.827
Colombia	−0.000 (0.001)	0.000*** (0.000)	0.792*** (0.026)	0.021 (0.029)	–	8.729*** (2.362)	0.072 (0.048)	0.768	0.323	0.540	0.706	0.845	0.832	0.984
Croatia	−0.000 (0.002)	0.000*** (0.000)	0.679*** (0.049)	0.146*** (0.027)	–	5.590*** (0.868)	0.035 (0.047)	0.774	0.322	0.483	0.479	0.355	0.371	0.991
Czech	−0.000 (0.003)	−0.200*** (0.034)	0.968*** (0.005)	0.189*** (0.018)	0.047*** (0.012)	3.360*** (0.215)	0.044 (0.034)	0.399	0.638	0.171	0.816	0.323	0.784	0.356
Denmark	−0.000 (0.001)	0.000** (0.000)	0.913*** (0.018)	0.075*** (0.015)	–	6.280*** (1.198)	0.028 (0.043)	0.551	0.719	0.105	0.233	0.758	0.398	0.896
Estonia	−0.004 (0.004)	0.000*** (0.000)	0.734*** (0.023)	0.181*** (0.022)	–	3.117*** (0.163)	0.027 (0.033)	0.779	0.836	0.178	0.227	0.885	0.443	0.239
France	0.000 (0.001)	0.000** (0.000)	0.935*** (0.012)	0.056*** (0.012)	–	7.477*** (1.743)	0.028 (0.045)	0.636	0.695	0.711	0.531	0.348	0.388	0.400
Germany	0.000 (0.001)	0.000** (0.000)	0.363** (0.164)	0.067* (0.037)	–	7.227*** (1.576)	−0.002 (0.011)	0.912	0.461	0.962	0.492	0.843	0.392	0.805
Hungary	0.000 (0.001)	−0.163*** (0.034)	0.975*** (0.004)	0.189*** (0.014)	0.037*** (0.012)	4.168*** (0.412)	0.017 (0.037)	0.396	0.451	0.150	0.657	0.247	0.639	0.649
Indonesia	−0.000 (0.001)	−0.396*** (0.070)	0.940*** (0.010)	0.308*** (0.037)	0.106*** (0.015)	4.486*** (0.497)	0.128*** (0.041)	0.732	0.924	0.772	0.296	0.706	0.449	0.828
Ireland	0.001 (0.000)	0.000*** (0.000)	0.782*** (0.018)	0.203*** (0.020)	–	4.188*** (0.411)	−0.064 (0.043)	0.186	0.893	0.516	0.608	0.123	0.433	0.980
Italy	0.001 (0.002)	−0.331*** (0.088)	0.945*** (0.014)	0.230*** (0.026)	0.058*** (0.019)	6.318*** (1.169)	0.001 (0.043)	0.824	0.465	0.876	0.745	0.896	0.536	0.960
Japan	0.000 (0.001)	−1.135*** (0.205)	0.838*** (0.028)	0.413*** (0.045)	0.055** (0.027)	4.631*** (0.563)	0.088** (0.040)	0.281	0.861	0.286	0.273	0.463	0.523	0.558
Korea	−0.000 (0.001)	−0.251*** (0.069)	0.960*** (0.010)	0.282*** (0.035)	0.035** (0.017)	5.865*** (0.968)	0.123*** (0.047)	0.675	0.992	0.754	0.718	0.517	0.819	0.829
Lithuania	0.000 (0.001)	0.000*** (0.000)	0.815*** (0.019)	0.155*** (0.018)	–	3.950*** (0.369)	−0.012 (0.034)	0.538	0.621	0.542	0.431	0.437	0.355	0.498
Malaysia	−0.000 (0.001)	−0.227*** (0.061)	0.964*** (0.009)	0.239*** (0.029)	0.038*** (0.012)	4.912*** (0.630)	0.091** (0.044)	0.341	0.884	0.561	0.520	0.327	0.384	0.999
Mexico	−0.000 (0.001)	0.000*** (0.000)	0.705*** (0.077)	0.180*** (0.025)	–	7.744*** (1.755)	0.136*** (0.049)	0.726	0.458	0.891	0.992	0.633	0.996	0.980

	Mean	Variance				Skew T		Goodness-of-Fit						
	a_0	ω	β	α	γ	υ	ζ	LB(10)	LM(10)	m1	m2	m3	m4	CvM
Netherlands	0.000 (0.001)	0.000** (0.000)	0.908*** (0.021)	0.063*** (0.013)	–	6.248*** (1.197)	0.028 (0.041)	0.475	0.949	0.473	0.412	0.639	0.558	0.469
Norway	−0.000 (0.001)	0.000*** (0.000)	0.907*** (0.018)	0.074*** (0.015)	–	5.332*** (0.843)	0.015 (0.036)	0.562	0.973	0.220	0.645	0.739	0.820	0.150
Panama	−0.000 (0.001)	0.000*** (0.000)	0.825*** (0.023)	0.132*** (0.018)	–	6.949*** (1.436)	0.006 (0.050)	0.786	0.254	0.486	0.553	0.645	0.624	0.992
Peru	−0.000 (0.001)	0.000*** (0.000)	0.792*** (0.025)	0.133*** (0.019)	–	4.471*** (0.495)	0.086** (0.042)	0.595	0.753	0.537	0.670	0.602	0.627	0.998
Philippines	−0.000 (0.001)	−0.375*** (0.064)	0.944*** (0.009)	0.324*** (0.037)	0.094*** (0.016)	5.190*** (0.705)	0.096** (0.047)	0.340	0.966	0.440	0.871	0.438	0.605	0.884
Poland	−0.000 (0.001)	−0.337*** (0.100)	0.948*** (0.015)	0.182*** (0.023)	0.057*** (0.013)	4.734*** (0.570)	0.066 (0.043)	0.462	0.844	0.110	0.346	0.388	0.374	0.799
Portugal	0.005 (0.005)	−0.228*** (0.052)	0.962*** (0.008)	0.228*** (0.030)	0.052*** (0.019)	4.975*** (0.685)	−0.016 (0.041)	0.713	0.992	0.600	0.563	0.560	0.510	0.768
Romania	−0.000 (0.001)	−0.400*** (0.091)	0.942*** (0.012)	0.214*** (0.019)	0.059*** (0.015)	3.918*** (0.337)	0.065 (0.040)	0.360	0.914	0.367	0.318	0.236	0.390	0.914
Slovakia	0.000 (0.001)	−0.689*** (0.123)	0.896*** (0.018)	0.496*** (0.044)	0.079*** (0.027)	3.817*** (0.327)	0.047 (0.037)	0.416	0.657	0.565	0.496	0.540	0.851	0.431
Slovenia	0.000 (0.001)	0.000*** (0.000)	0.728*** (0.016)	0.234*** (0.023)	–	3.117*** (0.158)	0.075** (0.035)	0.442	0.883	0.078	0.365	0.319	0.638	0.415
Spain	0.001 (0.002)	0.000*** (0.000)	0.828*** (0.033)	0.117*** (0.021)	–	6.733*** (1.340)	−0.062 (0.047)	0.725	0.882	0.592	0.532	0.809	0.326	0.959
Sweden	−0.001 (0.001)	−0.025 (0.039)	0.994*** (0.006)	0.119*** (0.025)	−0.038*** (0.011)	5.616*** (0.945)	−0.037 (0.042)	0.799	0.894	0.355	0.664	0.802	0.382	0.453
Thailand	−0.000 (0.003)	−0.259*** (0.071)	0.962*** (0.010)	0.252*** (0.030)	0.039** (0.017)	6.593*** (1.303)	0.056 (0.046)	0.904	0.963	0.509	0.680	0.820	0.986	0.807
U.K.	−0.001 (0.001)	0.000*** (0.000)	0.716*** (0.045)	0.179*** (0.023)	–	5.677*** (0.925)	−0.064 (0.044)	0.567	0.834	0.471	0.463	0.381	0.513	0.981
U.S.	−0.000 (0.002)	0.000*** (0.000)	0.809*** (0.030)	0.134*** (0.024)	–	3.576*** (0.266)	0.043 (0.036)	0.252	0.979	0.827	0.117	0.673	0.401	0.310
Vietnam	−0.000 (0.001)	0.000*** (0.000)	0.787*** (0.028)	0.148*** (0.023)	–	5.104*** (0.689)	0.026 (0.048)	0.571	0.937	0.421	0.955	0.340	0.955	0.999

This table shows the estimation results of the marginal distributions described in Section 3.3.1. Sovereign CDS returns are sampled at a daily frequency. The sample period is from December 01, 2009 to October 31, 2012. Standard errors are reported in parentheses. The standardized residuals are checked for autocorrelation and ARCH effect using the Ljung-Box test and Engel's LM test at lag 10. υ and ζ are the degrees of freedom parameter and the asymmetry parameter in Hansen (1994) skewed t distribution. The first four moments of $(u_t\text{-}u)^j$ are checked for i.i.d. assumption. m1, m2, m3, m4 stand for the p-values of Ljung-Box tests deployed on the first four moments of $(u_t\text{-}u)^j$ at lag 10 (Fei et al., 2017). Cramér-von Mises test is used to exam whether the transforms are Uniform(0,1) distributed. ***, ** and * denote significance at the 1%, 5%, and 10% level, respectively.

is collected from the Bank for International Settlements (BIS). BIS reports two types of banking statistics. One is calculated on an ultimate risk basis and the other is calculated on an immediate borrower basis. We use the following example to illustrate the difference. A U.S. bank extends a loan to a company based in France, and this loan is guaranteed by a German bank. On an ultimate risk basis, the loan is considered a claim of the U.S. bank on Germany, as Germany is where the ultimate risk resides. On an immediate borrower basis, this loan is considered a claim of the U.S. bank on France since the immediate borrower resides in France. We use the consolidated statistics with residency of the ultimate obligor. The BIS consolidated banking statistics are denominated in million U.S. dollars and reported at a quarterly frequency. We rescale them into trillion U.S. dollars because our tail dependence coefficient is within the range of zero to one. If we use the bank exposure data directly, the estimated coefficient will be too small to report. The BIS consolidated banking statistics are also used in other papers, such as Kallestrup et al. (2016), to construct the risk weighted exposure matrix. Specifically, Kallestrup et al. (2016) construct the risk weighted foreign exposures of banks in developed economies and find sovereign CDS spreads are significantly affected by the foreign exposures of their domestic banks. In our case, a more distressed economy to which the U.S. banks are exposed, more risk could be transferred to the U.S. banking system through the U.S. banks' foreign exposures. This would further harm the U.S. economy and increase the U.S. sovereign credit risk.

The trade flow stands for the trade flow (gravity model) between the U.S. and country$_j$, which is measured as the ln GDP of U.S. and the ln GDP of country$_j$ minus the ln (Geopraphical distance between the two countries) following Karnaukh et al. (2015). We also include two explanatory variables, financial dependence and international debt-to-GDP ratio, which relate to the international debt securities amount. The financial dependence is constructed as the ratio of a country's financial sector's international debt securities to the entire economy's international debt securities amount. It measures how heavily a country's financial system relies on external financing with respect to the external financing of the entire economy. Risk can transfer through the holding of international debt securities. For instance, a distressed financial corporation will suffer a cut in the debt value. This could reduce the wealth of foreign investors, such as U.S. investors, who hold these debts. If

Table 3.4 – Goodness-of-Fit of Dynamic Copulas: AIC

Dynamic Western Europe	Gaussian	Student's t	Gumbel
Austria	−159.367	**−161.098**	−128.140
Belgium	−155.262	**−160.131**	−134.690
Denmark	−148.059	**−153.486**	−131.440
France	−176.911	**−185.024**	−158.779
Germany	−161.816	**−170.490**	−145.881
Italy	−147.769	**−153.861**	−134.525
Netherlands	−161.816	**−171.158**	−146.516
Portugal	−88.795	**−93.617**	−79.620
Spain	−113.124	**−117.496**	−104.048
Ireland	−98.463	**−101.768**	−85.118
Sweden	−129.462	**−133.162**	−117.782
Norway	−126.277	**−130.489**	−109.575
U.K.	−172.017	**−180.191**	−156.808

Dynamic Central & Eastern Europe	Gaussian	Student's t	Gumbel
Bulgaria	−94.524	**−96.817**	−85.359
Croatia	**−91.159**	−91.122	−77.297
Estonia	−56.533	**−58.357**	−57.792
Hungary	−77.228	**−78.849**	−62.971
Lithuania	−79.749	**−84.215**	−75.092
Poland	−97.020	**−103.406**	−92.066
Romania	−87.286	**−88.955**	−79.365
Slovakia	−85.604	**−85.613**	−74.849
Slovenia	−44.037	**−46.323**	32.828
Czech	−93.919	**−96.838**	−90.323

Dynamic Asia	Gaussian	Student's t	Gumbel
China	**−80.583**	−79.785	−57.573
Indonesia	**−60.492**	−60.138	−39.809
Korea	**−78.585**	−77.786	−54.590
Malaysia	−82.260	**−82.680**	−61.853
Phillippines	−84.829	**−86.103**	−60.746
Thailand	−72.466	**−78.619**	−55.236
Vietnam	−70.229	**−70.657**	−43.795
Japan	−56.356	**−57.647**	−54.066

Dynamic Latin America	Gaussian	Student's t	Gumbel
Brazil	−53.776	**−55.222**	−46.380
Colombia	−51.425	**−54.887**	−44.571
Mexico	−47.067	**−47.404**	−33.550
Panama	−63.186	**−63.308**	−54.537
Peru	−31.153	**−34.566**	−24.980

This table reports the AIC statistics of dynamic Gaussian, Student's t, and Gumbel copulas for paired U.S.−Country$_j$ sovereign CDS returns. Country$_j$, j∈[1,36], refers to each of the 36 countries (from four regions) introduced in Section 3.2.3. AIC refers to the Akaike Information Criterion. The dynamic formations of copulas follows Patton (2006), where the time-varying dependence structure follows an ARMA(1,10) process. For each pair, bold font denotes the best selected copula formulation. The time series covers the period from December 01, 2009 to October 31, 2012.

the debt amount is large, this could have a negative impact on the economy of the countries in which foreign investors reside. We also include the international debt-to-GDP ratio, which is calculated as the entire economy's international debt securities to its GDP. This variable is included as a control variable for a country's indebtedness. The quarterly data of international debt securities are collected from BIS debt securities statistics.

To give a better illustration of the explanatory variables, we use the following example. If we focus on the tail dependence coefficient of a U.S.−German sovereign CDS pair, the bank foreign exposure is the consolidated foreign claims of the U.S. banking system on all residents, including the public sector, banks, and non-bank private sector, of Germany. The trade flow factor measures the trade flow between the U.S. and Germany, which is constructed using the same method as shown in Karnaukh et al. (2015). Financial dependence is calculated as the ratio of the German's financial sector's international debt securities to the total international debt securities amount of Germany. The international debt-to-GDP ratio is the German international debt securities to GDP ratio.

3.5 Results

3.5.1 Marginal Distribution Models

Table 3.3 reports the estimation results of the marginal distribution models. We know that the EGARCH model extends the standard GARCH model to incorporate asymmetric volatility. It captures the asymmetric volatility through γ. Specifically, CDS return series estimated with a positively significant leverage parameter γ implies that the volatility increases more in response to a positive shock than to a negative shock. The estimation results shown in Table 3.3 suggest that 15 out of 37 sovereign CDS return series in our sample contain this feature. We choose GARCH(1,1) over EGARCH(1,1) if the estimated γ is insignificant. Table 3.3 shows that 21 out of 37 sovereign CDS return series choose the GARCH(1,1) model. This means there is no significant asymmetric volatility feature that must be considered when modelling the marginal distributions for those sovereign CDS return series.

The leverage parameter γ is negatively significant at the 1% level for Sweden, which is different from the estimation results of the other 36 sovereign CDS returns. To investigate this issue, we first check the accuracy of Sweden sovereign CDS data and then validate the negative leverage parameter γ by re-estimating the Sweden sovereign CDS returns using another asymmetric volatility model GJR(1,1). To be specific, we first re-collect the Sweden sovereign CDS data from CMA and re-calculate the mid-quotes. We confirm that the Sweden sovereign CDS data used for the estimation of marginal distribution are correct. Second, we validate the accuracy of the negative leverage parameter γ in the EGARCH(1,1) using GJR(1,1). The estimation result of GJR(1,1) model's leverage parameter confirms the accuracy of the negative leverage parameter γ in EGARCH(1,1) model. To be specific, the estimated result for the GJR(1,1) model's $[\omega, \alpha, \beta, \gamma]$ set is [0.000,0.033***,0.943***,0.042***], where *** denotes significance at the 1% level. γ is positively significant at the 1% level. A positively significant γ in the GJR(1,1) model implies that volatility increases more in response to a negative shock than to a positive shock. This is consistent with the economic interpretation of the negative leverage parameter γ in the EGARCH(1,1) model. Therefore, we conclude that the negative leverage parameter γ in EGARCH(1,1) for Sweden sovereign CDS returns is correct. Moreover, we find that there are some comparably large decreases in Sweden sovereign CDS spreads in October 2012. To further investigate whether the negative γ is driven by these data points, we delete the Sweden sovereign CDS returns in October 2012 and re-estimate the marginal distribution model. We find that the leverage parameter γ in EGARCH(1,1) is still negative, but the significance level has decreased from 1% to 10%. We further investigate whether these large decreases in Sweden sovereign CDS spreads are caused by the changes in credit rating. We collect the S&P, Moody, and Fitch's credit ratings from Bloomberg and find that all the ratings for Sweden remain unchanged during our sample period. This leads us to conclude that credit rating is not the source for these large drops in Sweden sovereign CDS spreads. We suspect that these features of large decreases in Sweden sovereign CDS spreads might be due to Sweden's good credit quality, which leads to a higher likelihood of getting large drops in Sweden CDS spreads rather than jumps. Nevertheless, the negative leverage parameter γ suggests that volatility increases more in response to a negative shock than to a positive shock for Sweden sovereign CDS returns.

Table 3.5 – Tail Dependence Coefficients: Western Europe, Central & Eastern Europe, Latin America, and Asia

				Panel A: Western Europe				
$\lambda^U = \lambda^L$	Austria	Belgium	France	Germany	Ireland	Italy	Netherlands	Norway
	0.021	0.053	0.088	0.068	0.022	0.045	0.076	0.040
$\lambda^U = \lambda^L$	Portugal	Spain	Sweden	U.K.	Denmark			
	0.031	0.033	0.034	0.083	0.052			
				Panel B: Central & Eastern Europe				
$\lambda^U = \lambda^L$	Bulgaria	Croatia	Czech	Estonia	Hungary	Lithuania	Poland	Romania
	0.020	0.000	0.022	0.007	0.012	0.029	0.039	0.016
$\lambda^U = \lambda^L$	Slovakia	Slovenia						
	0.003	0.008						
				Panel C: Latin America				
$\lambda^U = \lambda^L$	Brazil	Colombia	Mexico	Panama	Peru			
	0.008	0.014	0.002	0.003	0.010			
				Panel D: Asia				
$\lambda^U = \lambda^L$	China	Indonesia	Japan	Korea	Malaysia	Phillipines	Thailand	Vietnam
	0.000	0.000	0.007	0.000	0.005	0.011	0.033	0.004
				Panel E: Regional Average				
$\lambda^U = \lambda^L$	Western Europe	Central & Eastern Europe	Latin America	Asia				
	0.049	0.016	0.007	0.007				

This table reports the tail dependence coefficients of 36 U.S.−Country$_j$ sovereign CDS pairs. The 36 countries include: 13 Western European countries, 10 Central & Eastern European countries, 5 Latin American countries, and 8 Asian countries. The tail dependence coefficient is calculated from the best selected copulas shown in Table 3.4 and shown in average value. λ^U and λ^L refer to the upper and lower tail dependence coefficients. $\lambda^U = \lambda^L$ indicates symmetric tail dependence and it holds for each of CDS pairs because Table 3.4 shows the best copula is either the Student's or Gaussian. Panel E reports the regional tail dependence coefficient calculated as the cross-sectional average value.

We follow Diebold et al. (1998) to evaluate whether the marginal distribution is correctly specified. Diebold et al. (1998) suggest û should be i.i.d. uniform(0,1) distributed if the marginal distribution is correctly specified. This is tested in two steps: first, we exam the serial correlation of the first four moments of (û-ū)^j, j∈{1,2,3,4} using LB(10) statistics (Fei et al., 2017). Second, we test the null hypothesis that û is uniform(0,1) using the Cramér-von Mises test (Reboredo, 2011, 2012, 2013). m1, m2, m3, and m4 in Table 3.3 are the p-values of the Ljung-Box tests on the first four moments of the probability integral transformations (û-ū)^j, j∈{1,2,3,4} at lag 10. P-values are all above 0.05, which suggest we cannot reject the i.i.d. assumption at the 5% significance level for all series. P-values of the Cramér-von Mises tests on the CDS return series are also all above 0.05, which indicate that the null hypothesis that the transforms are Uniform(0,1) distributed cannot be rejected at the 5% significance level for all series. Moreover, the p-values of the LB(10) and LM(10) tests show that neither autocorrelation nor ARCH effects remain in the filtered standardized residuals. Overall, the results of goodness-of-fit suggest our marginal distribution models are not mis-specified and copula models can correctly capture the co-movement between sovereign CDS returns.

3.5.2 Copula Models

Table 3.4 reports the AIC statistics of the dynamic copula models. For each pair, the best copula is indicated by the smallest AIC and expressed in bold font. The results show that the best copula is either the Student's t or Gaussian. This provides evidence of symmetric tail dependence for all 36 U.S.−Country$_j$ sovereign CDS pairs. In other words, the upper tail dependence coefficient has the same value as the lower tail dependence coefficient for each of the 36 U.S.−Country$_j$ sovereign CDS pairs. In fact, only four sovereign CDS pairs, U.S.−Croatia, U.S.−China, U.S.−Indonesia, and U.S.−Korea, choose the dynamic Gaussian copula. The U.S.−Croatia sovereign CDS pair is the only U.S.−European sovereign CDS pair that chooses the Gaussian copula. The remaining three pairs are all U.S.−Asian sovereign CDS pairs. The Gaussian copula has a tail dependence coefficient of zero. Hence, the tails are independent for these four sovereign CDS pairs.

The tail dependence coefficients of the best selected copulas for all 36 U.S.−Country$_j$ sovereign CDS pairs are shown in Table 3.5 Panel A to Panel D. Each U.S.−Country$_j$ sovereign CDS pair is represented by the name of Country$_j$. The average tail dependence coefficients of four regions are calculated as the cross-sectional average and represented in Table 3.5 Panel E. $\lambda^U = \lambda^L$ refers to the symmetric tail dependence because our best selected copula for each of the sovereign CDS pairs is either the Student's t or Gaussian. We can draw several conclusions from the results: first, the tail dependence coefficients of U.S.−European sovereign CDS pairs are higher than the tail dependence coefficients of U.S.−Asian and U.S.−Latin American sovereign CDS pairs. As shown in Table 3.5 Panel D and Panel C, for the majority of the U.S.−Asian and U.S.−Latin American sovereign CDS pairs, the tail dependence coefficients are close to zero. In fact, the average tail dependence coefficients of U.S.−Asian and U.S.−Latin American sovereign CDS pairs are both 0.007, as shown in Table 3.5 Panel E, while the tail dependence coefficients of U.S.−Western European sovereign CDS pairs are 0.049. Second, the tail dependence coefficients of U.S.−Western European sovereign CDS pairs are higher than those of U.S.−Central

Table 3.6 – Cross−Sectional Analysis

Panel A: Monthly Frequency						
	(1)	(2)	(3)	(4)	(5)	(6)
Bank foreign exposure	0.120** (0.036)		0.092** (0.030)	0.057** (0.019)	0.056** (0.018)	0.058** (0.019)
Financial dependence		0.040** (0.011)	0.025* (0.010)	0.001 (0.009)		0.005 (0.009)
Trade flow				0.010** (0.002)	0.010** (0.002)	0.009** (0.002)
International debt/GDP						−0.000 (0.001)
Intercept	0.029** (0.004)	0.016** (0.005)	0.018** (0.005)	−0.016 (0.010)	−0.017 (0.010)	−0.015 (0.010)
Time FE	YES	YES	YES	YES	YES	YES
Observations	770	770	770	770	770	770
Adj. R^2	0.453	0.351	0.536	0.689	0.690	0.696
Panel B: Quarterly Frequency						
	(1)	(2)	(3)	(4)	(5)	(6)
Bank foreign exposure	0.120** (0.035)		0.092** (0.029)	0.057** (0.018)	0.057** (0.018)	0.058** (0.018)
Financial dependence		0.040** (0.011)	0.025* (0.010)	0.001 (0.010)		0.004 (0.009)
Trade flow				0.010** (0.002)	0.010** (0.002)	0.009** (0.002)
International debt/GDP						−0.000 (0.001)
Intercept	0.029** (0.004)	0.016** (0.005)	0.018** (0.005)	−0.016 (0.009)	−0.016 (0.010)	−0.015 (0.010)
Time FE	YES	Yes	Yes	Yes	Yes	Yes
Observations	264	264	264	264	264	264
Adj. R^2	0.460	0.347	0.574	0.708	0.709	0.709

This table reports results from a panel regression with time-fixed effects of the tail dependence coefficients on explanatory variables, sampled monthly and quarterly. The regression specification is given by eq(3.6). The explanatory variables include bank foreign exposure, trade flow, financial dependence, and the international debt-to-GDP ratio. A detailed definition of these variables is shown in Section 3.4. We report the adjusted R^2 of the regression. The standard errors are clustered by country following Augustin et al. (2016) and reported in parentheses. Significance levels at the 1% and 5% are denoted by ** and *, respectively.

& Eastern European sovereign CDS pairs. In fact, the highest tail dependence coefficient is that for the U.S.−France sovereign CDS pair (0.088). The other high tail dependence coefficients are also for U.S.−Western European sovereign CDS pairs, including U.S.−U.K., U.S.−Germany, and U.S.−Netherlands. Overall, we conclude that the probability of simultaneous large increases in the U.S. and Western European sovereign credit risks is the highest among all regions, while the tail dependence coefficients between U.S.−Asian and U.S.−Latin American sovereign CDS pairs are in general close to zero. Therefore, we do not further consider the tail dependence coefficient series from these two regions in our cross-sectional analysis. Moreover, we also exclude the tail dependence coefficient of the U.S.−Croatia sovereign CDS pair because it chooses the dynamic Gaussian as the best selected copula, which indicates that the tail dependence coefficient is zero.

3.5.3 Determinants of Co-Dependence

The results of our cross-sectional analysis with monthly and quarterly frequencies are presented in Table 3.6 Panel A and Panel B. We first look at the results in Panel A. The univariate regression results in column (1) show that there is a statistically significant relationship between the U.S. banks' foreign exposure[12] and the tail dependence coefficients of the U.S.−European sovereign CDS pairs[13]. The results show that larger foreign exposure of the U.S. banking system is associated with a higher probability of large joint increases in the sovereign credit risks of the U.S. and European countries. The results in Table 3.6 column (2) and column (3) show that there is a statistically significant relationship between financial dependence[14] and the tail dependence coefficient. This significant relationship remains after controlling for the bank's foreign exposure. We include trade flow[15] into the regression analysis, and the estimation results are shown in Table 3.6 column (4). The results show that the coefficient on trade flow is statistically significant at the 1% level, while the coefficient on financial dependence becomes statistically insignificant. We further drop financial dependence and only consider U.S. banks' foreign exposure and trade flow in our regression analysis. The estimation results are shown in Table 3.6 column (5). We find that both coefficients are statistically significant at the 1% level. To test whether the explanatory power of these two variables remain after controlling for other explanatory variables, we include both the international debt-over-GDP ratio and financial dependence in our regression analysis. The results are shown in Table 3.6 column (6). The results show that the coefficients of U.S. banks' foreign exposure and trade flow remain to be statistically significant at the 1% level after controlling for the other two factors. To summarize the results from the monthly

[12]The U.S. banks' foreign exposure is the consolidated foreign claims of the U.S. banking system on all residents, including the public sector, banks, and non-bank private sector, of another European country. A detailed illustration of foreign exposure can be found in Section 3.4.

[13]Recall that we only include the tail dependence coefficients of U.S.−European sovereign CDS pairs in our cross-sectional analysis because the tail dependence coefficients of U.S.−Asian and U.S.−Latin American sovereign CDS pairs are close to zero. A close to zero tail dependence coefficient suggests that the tail is nearly independent.

[14]The financial dependence is constructed as the ratio of a European country's financial sector's international debt securities to the total international debt securities amount of that country. It measures how heavily a country's financial system relies on external financing w.r.t. the external financing of the entire economy.

[15]The trade flow is the trade flow (gravity model) between the U.S. and European country, which is measured following Karnaukh et al. (2015).

cross-sectional analysis. We find higher trade flow and larger foreign exposure of the U.S. banking system are associated with a higher probability of large joint increases in the sovereign credit risks of the U.S. and European countries. Turning to the quarterly regression results in Panel B, they are essentially the same as the estimation results of the monthly regression. Therefore, we conclude that our findings are quite robust.

3.6 Conclusion

We use this current paper to study the dependence structure of sovereign CDS spreads between the U.S. and 36 countries. These 36 countries covers four different regions, such as: Western Europe, Central & Eastern Europe, Asian, and Latin America. Our analysis is carried out for the December 2009 to October 2012 period. We choose December 2009 as the start of sample period to avoid the potential structure breaks caused by the introduction of trading standardized CDS contracts of U.S., Western European, Emerging European & Latin American, and Asian sovereign CDSs. October 2012 is used as the end of our sample period to avoid the potential structural break introduced by the implementation of the 2012 EU permanent short-selling ban. Moreover, this period is also associated with an increasing/highest net notional amount outstanding of U.S. sovereign CDS, which implies that investors pay more/most attention to this contract during this period. Using the dynamic Gaussian, Student's t, and Gumbel copula models, we obtain the time-varying tail dependence coefficients for each of the 36 U.S.$-$Country$_j$ sovereign CDS pairs. We focus our study on the tail dependence coefficient because it allows us to study the joint extreme movements of default probabilities (sovereign credit risk) (Meine et al., 2016). To further analyze the determinants of the tail dependence coefficient, we perform a cross-sectional analysis. Specifically, our empirical analysis is a panel regression with time-fixed effects of the tail dependence coefficients on explanatory variables. We include four explanatory variables: bank foreign exposure, trade flow, financial dependence, and international debt-to-GDP ratio. The cross-sectional analysis is performed with both monthly and quarterly frequencies.

There are several conclusions we can draw from the results of the copula models and the panel regressions. First, for each of the U.S.$-$Country$_j$ sovereign CDS pairs, the best copula is either the Student's t or Gaussian. This implies that the tail dependence is symmetric for all sovereign CDS pairs. In other words, the upper and lower tail dependence coefficients have the same value. Second, the average tail dependence coefficients of U.S.−European sovereign CDS pairs is higher than the average tail dependence coefficients of U.S.−Asian and U.S.−Latin American sovereign CDS pairs. In fact, three of U.S.−Asian sovereign CDS pairs have tail dependence coefficients of zero. Considering the tail dependence coefficients of U.S.−European sovereign CDS pairs in our cross-sectional analysis, we find that higher trade flow and larger foreign exposure of the U.S. banking system are associated with a higher probability of large joint increases in the sovereign credit risks of the U.S. and European countries.

Our results have several implications for academics, investors, and policymakers. For academics, we establish the foundation for studying the dynamics and the determinants of the tail dependence coefficients of sovereign CDS pairs. For investors and policymakers, our results suggest monitoring the U.S. banking system's foreign exposure and the risk of trade counterpart is important for measuring the co-dependence of the sovereign credit risks between the U.S. and other countries.

Bibliography

Atil, A., Bradford, M., Elmarzougui, A., Lahiani, A., 2016. Conditional dependence of US and EU sovereign CDS: A time-varying copula-based estimation. *Finance Research Letters* 19, 42-53.

Augustin, P., Sokolovski, V., Subrahmanyam, M.G., Tomio, D., 2016. Why do investors buy sovereign default insurance? *CFS Working Paper 540*, Center for Financial Studies.

Avino, D., Cotter, J., 2014. Sovereign and bank CDS spreads: Two sides of the same coins. *Journal of International Financial Markets, Institutions & Money* 32, 72-85.

Blommestein, H., Eijffinger, S., Qian, Z.X., 2016. Regime-dependent determinants of Euro area sovereign CDS spreads. *Journal of Financial Stability* 22, 10-21.

Chernov, M., Schmid, L., Schneider, A., 2017. A macrofinance view of U.S. sovereign CDS premiums. *Working Paper*, UCLA and Duke University.

Chollete, C., Peña, V.D.L., Lu, C.C., 2011. International diversification: A copula approach. *Journal of Banking* & *Finance* 35 (2), 403-417.

Diebold, F.X., Gunther, T.A., Tay, A.S., 1998. Evaluating density forecasts with applications to financial risk management. *International Economic Review* 39 (4), 863-883.

Dieckmann, S., Plank, T., 2012. Default risk of advanced economies: An empirical analysis of credit default swaps during the financial crisis. *Review of Finance* 16 (4), 903-934.

Engle, R., 1982. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica* 50 (4), 987-1007.

Fei, F., Fuertes, A.M., Kalotychou, E., 2017. Dependence in credit default swap and equity markets: Dynamic copula with Markov-switching. *International Journal of Forecasting* 33 (3), 662-678.

Fontana, A., Scheicher, M., 2016. An analysis of euro area sovereign CDS and their relation with government bonds. *Journal of Banking & Finance* 62, 126-140.

Glosten, L. R., Jagannathan, R. and Runkle, D.E., 1993. On the relation between the expected value and the volatility of the nominal excess return on stocks. *Journal of Finance* 48 (5), 1779-1801.

Hansen, B.E., 1994. Autoregressive conditional density estimation. *International Economic Review* 35 (3), 705-730.

Haworth, H., 2011. A guide to credit events and auctions. *Credit Suisse Fixed Income Research*.

International Monetary Fund., 2013. A new look at the role of sovereign credit default swaps. *Global Financial Stability Report*.

Joe, H., 2005. Asymptotic efficiency of the two-stage estimation method for copula-based models. *Journal of Multivariate Analysis* 94 (2), 401-419.

Kallestrup, R., Lando, D., Murgocic, A., 2016. Financial sector linkages and the dynamics of bank and sovereign credit spreads. *Journal of Empirical Finance* 38, 374-393.

Karnaukh, N., Ranaldo, A., Söderlind, P., 2015. Understanding FX liquidity. *Review of Financial Studies* 28 (11), 3073-3108.

Meine, C., Supper, H., Weiß, G., 2016. Is tail risk priced in credit default swap premia? *Review of Finance* 20 (1), 287-336.

Markit, 2009. Forthcoming CDS convention changes for Japan and Asia, *Markit Group*.

Oh, D.H., Patton, A.J., 2016. Time-varying systemic risk: Evidence from a dynamic copula model of CDS spreads. *Journal of Business & Economic Statistics* 36 (2), 181-195.

Patton, A.J., 2006. Modelling asymmetric exchange rate dependence. *International Economic Review* 47 (2), 527-556.

Patton, A.J., 2013. Copula methods for forecasting multivariate time series. *Handbook of Economic Forecasting* 2, 899-960.

Reboredo, J.,C., 2011. How do crude oil prices co-move? A copula approach. *Energy Economics* 33 (5), 948-955.

Reboredo, J.,C., 2012. Modelling oil price and exchange rate co-movements. *Journal of Policy Modelling* 34 (3), 419-440.

Reboredo, J.,C., 2013. Is gold a safe haven or a hedge for the US dollar? Implications for risk management. *Journal of Banking & Finance* 37, 2665-2676.

Zhu, H.M. Li, R., Li, S., 2014. Modelling dynamic dependence between crude oil prices and Asia-Pacific stock market returns. *International Review of Economics and Finance* 29, 208-223.

Appendix

Copula Formulations

1. **Gaussian Copula(Elliptical)** The bivariate Gaussian copula cdf is defined as:

$$C(u_1,u_2;\rho) = \int_{-\infty}^{\Phi^{-1}(u_1)} \int_{-\infty}^{\Phi^{-1}(u_2)} \frac{1}{2\pi\sqrt{1-\rho^2}} \exp\left(\frac{2\rho rs - r^2 - s^2}{2(1-\rho^2)}\right) drds$$

   where Φ^{-1} is the inverse of univariate standardized Gaussian cumulative distribution function and ρ is the Pearson's correlation coefficient. The coefficients of lower and upper tail dependence for the Gaussian copula are $\lambda^U = \lambda^L = 0$. The implied Kendall's τ is $\frac{2}{\pi} arcsin(\rho)$.

2. **Student's t Copula(Elliptical)** The bivariate Student's t copula cdf is defined as:

$$C(u_1,u_2;\rho,v) = \int_{-\infty}^{t_v^{-1}(u_1)} \int_{-\infty}^{t_v^{-1}(u_2)} \frac{1}{2\pi\sqrt{1-\rho^2}} \left(1+\frac{r^2 + s^2 - 2\rho rs}{v(1-\rho^2)}\right)^{-\frac{v+2}{2}} drds$$

   where t_v^{-1} is the inverse of Student's t cumulative distribution function with $v > 2$ degrees of freedom. Student's t copula captures symmetric upper and lower tail dependencies. $\lambda^U = \lambda^L = 2 * t_{v+1}(-\sqrt{v+1}\sqrt{\frac{1-\rho}{1+\rho}})$, where t_{v+1} denotes the cdf of a univariate Student's t distribution with $v + 1$ degrees of freedom. A stronger linear correlation ρ and a lower degree of freedom v lead to a stronger tail dependence. The implied Kendall's τ is $\frac{2}{\pi} arcsin(\rho)$.

3. **Gumbel Copula(Archimedean)** The bivariate Gumbel cdf is defined as:

$$C(u_1,u_2;\delta) = \exp\{-[(-\log u_1)^\delta + (-\log u_2)^\delta]^{\frac{1}{\delta}}\}$$

   where $\delta \in (1,\infty)$[16]. The coefficient of lower tail dependence is $\lambda^L = 0$, and

[16]Alternatively, δ can be defined as $\delta \in [1,\infty)$. When $\delta = 1$, we obtain the independence copula. Here we follow Patton (2013) and define the rang of δ as $\delta \in (1,\infty)$.

the coefficient of the upper tail dependence is $\lambda^U = 2 - 2^{\frac{1}{\delta}}$. The implied Kendall's τ is $\frac{\delta-1}{\delta}$.

YI LI

☎ *+41(0)78 754 6059*
✉ *yi.li@student.unisg.ch*

Editorial

Reviewer for *Risk Management*.

Conference

Presenter (all single-author papers):

– *2019 China Conference of CEA (UK/Europe), Shanghai, China*: Understanding China Sovereign Credit Default Swap.

– *2019 PiF Seminar (St.Gallen University), St.Gallen, Switzerland*: The Information Content of Volatility for Sovereign CDS: Evidence from the Western European Market (pervious version).

– *2018 PiF Seminar (St.Gallen University), St.Gallen, Switzerland*: Understanding China Sovereign Credit Default Swap.

– *2014 Topics in Finance Workshop, Davos, Switzerland*: Network Approach to Interbank Market: A Survey.

– *2019 Derivative Markets Conference, New Zealand* (Invitation Received).

– *2019 Asia-Pacific Conference on Economics & Finance, Singapore* (Invitation Received).

Education

2014-2020 Ph.D in Finance, University of St.Gallen, Switzerland.

2010-2012 Master of Science in Actuarial Science, HEC Lausanne, Switzerland. *Teaching Assistant in Finance, Course: Principles of Finance, 2011-2012*

2005-2009 Bachelor of Science in Economics, HuaZhong Normal University, China.

Computer Skills

Python, JMP, Matlab, R, LaTeX, VBA, C, SQL, Office.