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TRABAJO FIN DE GRADO EN
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A GRANGER CAUSALITY ANALYSIS OF THE LEAD-LAG RELATIONSHIP BETWEEN THE STOCK MARKET AND THE SOVEREIGN CDS MARKET IN CHINA

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Abstract: The present study provides an investigation of the lead-lag relationship between the Chinese sovereign credit default swap (CDS) market and the Chinese stock market over the period 2007-2020. The long sample allows for a thorough investigation of both crisis and non-crisis periods, while also considering crises of different nature, like the current sanitary crisis of COVID-19. For this, a VAR model has been used, enabling to analyse the connection patterns existing between the two markets through Granger causality tests over time. The results show that information transmission mechanisms are present between the two markets in periods of financial turmoil, although they appear to be time varying and dependent of the economic cycle.

Key words: stock market; CDS market; granger causality; rolling VAR model

Resumen: El objetivo del presente trabajo es analizar la conexión entre el mercado de credit default swaps (CDS) soberanos Chinos y el mercado de acciones Chino para el periodo 2007-2020. La larga muestra temporal permite llevar acabo un análisis exhaustivo de periodos de crisis y no-crisis, tendiendo en cuenta también crisis de naturaleza diferente. Para esto, se ha hecho uso de un modelo VAR, que permite analizar los patrones de conexión entre ambos mercados por medio de tests de causalidad de Granger para diferentes periodos de crisis y de calma. Los resultaos muestran que mecanismos de transmisión de información están presentes entre ambos mercados en periodos de tumulto financiero, aunque estos mecanismos parecen variar en el tiempo y depender del ciclo económico.

Palabras clave: mercado de valores; mercado de CDS; causalidad de granger; modelo VAR móvil

1. INTRODUCTION

During the financial turmoil of 2007 and 2008, the positive relationship between credit default swaps (CDSs), among other derivatives, and systemic risk became apparent. The Systemic Risk Centre at the London School of Economics defines systemic risk as "a breakdown of an entire system rather than simply the failure of individual parts. In a financial context, it captures the risk of a cascading failure in the financial sector, caused by interlinkages within the financial system, resulting in a severe economic downturn". Going back to the financial crisis of 2008, the default by some financial institutions created a "ripple effect" that led to defaults by other financial institutions, threatening the stability of the financial system (Hull, 2015). Since banks lend each other a lot in OTC markets, when one fails, its counterparty will take huge losses and will be in risk of failing too; at the same time, another bank who may have incurred transactions with the previous ones will experience harsh financial difficulties as a result, and this goes on.

The default correlation and systemic risk aforementioned are caused by various factors. One is the condition of the economy, and another is contagion. On the one hand, good macroeconomic conditions imply a lower default probability for companies, and consequently, higher levels of confidence for investors. The opposite holds for bad macroeconomic times. On the other hand, credit contagion is defined as the process whereby a problem in one sector of the world economy leads to the problem in other unrelated sectors (Hull, 2015). The credit crisis of 2008 saw this happen when the recession led to the default by many countries. In 2011, Greece was having trouble repay its debt, what made investors reluctant to buy debt to other countries like Ireland, Spain, Portugal, or Italy, causing an increase in their sovereign bond yield spreads to unsustainable levels. Broto and Perez-Quirós (2011) in an analysis of the effects of sovereign CDSs in the European subprime crisis provide evidence that, indeed, contagion and the overreaction of investors played a huge role in the spread of the crisis between the most affected European countries.

Furthermore, a concern about the possibility of Greece exiting the Euro and the subsequent rupture of the currency arose, making investors lose confidence. As these countries became unable to repay their debt or find financing for that purpose, and proceeded to bail out their biggest banks, the financial guarantees of the European Union became worried about the effects of a possible credit contagion and a subsequent collapse of the euro. Finally, the European Central Bank, the International Monetary Fund, and the European Stability Facility stepped in to rescue the aforementioned countries. These events put in evidence the fact that information and the way in which it is spread play a critical role in the markets and their correlation, as it affects greatly the confidence of investors and it is closely related to the transmission of systemic risk and credit contagion, like in the case for the European sovereign debt crisis.

All in all, the subprime crisis of 2007 put in evidence how intricately linked international financial markets were through this kind of derivatives, and the vulnerability that that caused in the international financial system. Credit risk was quickly transferred between financial institutions all around the world, deriving in the subsequent financial crisis of 2008, where international financial markets suffered great losses and distortions. The loss of confidence of investors derived in the lack of liquidity and the subsequent pronounced increase in the interest rates at which financial institutions made loans to each other. These happenings, along with the sovereign debt crisis of the Eurozone, revealed the need to study risk management, and specially, credit risk management and the way it relates to other stock markets. This thesis will revolve around this topic, trying to shed light to the connection between credit risk, with CDSs as a proxy, and the stock market. More specifically, the focus will be put in the Asian market, for which not much research on this topic has been carried out. The objective is to identify the transmission between the CDS market and the stock market and analyse the effects that crises, including the one we are currently experiencing with the COVID-19, have in the connection between the two markets.

Lastly, the mainstream research about the relationship between the stock and credit markets is very heterogeneous, no consensus has been reached over the cause-effect relationship between the stock and credit markets. While some studies suggest that stock markets lead CDS markets, with that causality increasing during periods of turmoil (Ballester and González-Urteaga, 2020, Byström, 2005, Fung et al., 2008, Forte and Peña, 2009, among others), others show the opposite relationship (Acharya and Johnson, 2007, Calice and Ioannidis, 2012, Narayan, 2015). The analysis on the topic is quite limited for Asian markets (Vashkevich and Basazinew, 2013, Chan, Zhang, and Fung, 2008) as it has been mainly focused on the US and the European Union (González-Urteaga & Ballester, 2020). Considering all of this, there is a clear necessity to add to this line of research.

The paper will be organized as follows. In section two, we will introduce the basic theoretical concepts related to the topics to be covered in the analysis, including an overview of risk –market risk, credit risk and their subcategories–, the different models of credit risk measurement, and the selected approach –CDS spreads– and the reasoning behind. In section three we will review previous literature on the topic of analysis. Section 4 will provide the analysis of the data, including an overall view of the basic statistics, an analysis of rolling correlations, and a rolling Granger causality test. Lastly, section 5 will provide some final conclusions.

2. BASIC CONCEPTS

In this section we will introduce the basic theoretical concepts related to the topics to be covered in this paper. We will start by introducing the different types of financial risks. Then, we will review the different methodologies used to measure credit risk, and we will finish by justifying the selection of CDSs as the proxy for credit risk.

2.1 Financial risk

From a general point of view, risk may be defined as the contingency, probability or proximity of a danger or harm. From an economic point of view, risk may be defined as the possibility of obtaining a different outcome from the one initially expected. From a financial point of view, risk refers to the uncertainty surrounding the ability of a firm to recover its initial investment.

The difference in the expected and realized outcomes might be due to various reasons, according to which we can derive different types of risk. These different types of risks do not appear indistinctively, instead, most of the times, they interact. If, for example, the risk premium of a bond issuer increases, its cost of financing will increase too, increasing the risk of future non-payment of its obligations as a consequence.

The two main categories of financial risk are discussed next, market risk and credit risk, paying especial attention to the latter since it is the main focus of the present research.

2.1.1 Market risk

Market risk comes from the risk of experiencing losses due to price fluctuations in capital markets, whether it be in the form of fluctuations in variable income, raw materials, interest rates, exchange rates, credit spreads, etc. It also comprises liquidity risk, which arises when the price of an asset has to be lowered significantly in order to be sold or purchased (Martínez, 2012).

Interest rate risk: It refers to fluctuations in interest rates in the opposite direction of the expected when the investment was made; this includes reinvestment risk too (the risk that when reinvesting an asset or its cash flows, the investor[1] will be forced to do so at lower interest rates than the expected).

[1] Here we use the term investor in a broad sense, referring to natural persons, legal persons, and sovereign states.

Spread risk: It is the condition or status of the issuer entity will affect the risk premium or the spread of its assets, decreasing their market value even if all payments are met and the interest rates remain stable.

Volatility risk: It refers to the risk that the volatility[2] of an asset will affect an asset's price negatively. The greater the volatility of an asset, the greater the volatility risk will be, as it will be more likely that the price of the asset will fluctuate either positively or negatively.

Exchange rate risk: It arises from the uncertainty regarding the price of the currency at which a transaction is going to be made. This risk will affect the counterparty that will have to pay a higher price in order to obtain the currency needed for the transaction, or the one that will receive less monetary units when exchanging the currency received as a result of the transaction. Exchange rates depend on many factors that should be considered before entering a transaction implying currency exchanges, like interest rates, inflation, the current account of a country or the information held by investors.

Inflation risk: It arises when purchasing power is lost due to greater-than-expected increases in inflation rates. Price raises also affect the value of the savings of investors.

Liquidity risk: It may be defined as the hardship to sell an asset rapidly at a value close to what is reasonable or to the hardships that an enterprise or country may face to obtain funds in order to face its obligations.

2.1.2 Credit risk

Before the global financial crisis and the European debt crisis not much attention was paid to this type of risk. After the crises exploded, however, financial markets suffered great distortions and their connection to credit derivatives became apparent, increasing the interest of scholars in understanding credit risk and its transmission to other financial markets.

Credit risk arises from the possibility that borrowers, bond issuers, and counterparties in derivatives transactions breach any of the payments due, whether nominal or interest payments. Overall, credit risk is determined by three principles (Bonàs, Llanes, Usón, & Veiga, 2007): the expected loss, the unexpected loss and the level of regulatory capital needed to protect from greater-than-expected losses.

[2] Volatility is defined as the capacity of an asset's price to fluctuate around its mean.

- Expected loss: the expected loss depends on the deterioration the assets are facing at the moment of the measurement. It depends, at the same time, on the institution's exposure[3], on the default probability[4], and on the severity[5].
- Unexpected loss: the unexpected loss is the deviation between the expected loss and the actual loss beared after the credit event, it may be considered a measure of volatility because of that. There are some elements of risk that may affect the level of unexpected loss, which are the volatility of the exposure, the volatility of the default, the volatility of the severity, the concentration of the exposure, and the correlations.
- The level of economic or regulatory capital: it comprises the minimum capital requirements in order to carry the operations while protecting the entity from greater-than-expected losses.

Figure 1 shows the form of the credit loss distribution given by the aforementioned factors. Note that the distribution is not symmetrical, it is highly skewed to the right, implying that there is a greater chance of bearing small losses and a smaller chance of bearing large losses. The distribution also has a heavy tail, implying that the chances of bearing large losses reduce slowly.

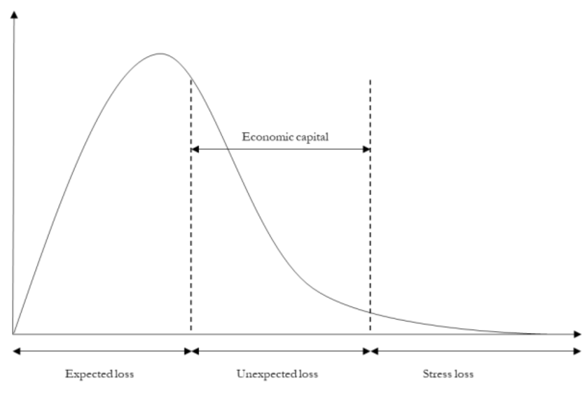

Figure 1 Credit loss distribution

We may also divide credit risk into different categories (see Figure 2):

Industry risk: It arises as a consequence of factors related to an industry's performance.

[3] It is the amount exposed to the credit event, usually measured with spreads provided by rating agencies' historical data (transition rates).
[4] It is the probability that a credit event might occur in a certain time period. It is related to the default ratings of the issuer. There are different types of credit events: bankruptcy, deferral, obligation default, debt restructuring, repudiation or moratorium, and obligation acceleration.
[5] It is the actual loss beared after a credit event. Normally, the amount of the loss the investor will bear will depend on the asset's ratings and on the type of default. Rating agencies provide historical data on recovery rates too.

Business risk: It arises when companies have trouble reaching their financial objectives and obligations.

Legal risk: It arises due to financial and/or reputational losses coming from overlooking legal frameworks, regulations, lawsuits, etc. It was considered an operational risk under Basel II[6].

Country risk: When the borrower, bond issuer, or counterparty is a state, we talk about country risk. It arises from the possible negative effect of the political, social, legal and cultural situation of a state on the value of foreign direct investment (Tellez & Martin, 2014). Country risk encompasses both the creditworthiness of the state itself, and the totality of the debt of the country, whether it be public or private debt (Mascareñas, 2004).

Political risk: It includes strict political risk (also referred to as socio-political risk) and administrative risk. It arises as a consequence of governmental acts and/or social and political forces of the country. It is related to political stability and consequently, elections and political regime changes affect it (Mascareñas, 2004).

Economic risk: It arises as a consequence of investments in foreign countries and is affected by macroeconomic factors (macroeconomical risk), or changes in business conditions (microeconomical risk).

Strict country risk: It arises after acquiring financial assets that have been emitted by foreign countries or after lending to residents in a third country. It can be further divided into sovereign risk and transfer risk (Mascareñas, 2004).

Sovereign risk: If we only focus on the creditworthiness of the state specifically, then we are referring to sovereign risk. Sovereign risk arises from the possibility that the state denies payment because of political motives or the lack of foreign currency (foreign reserves) to meet its obligations. In emerging economies, sovereign default could bring with it a chain of defaults, particularly credit and bank loan default, like in the case of Argentina in 2001 (Tellez & Martin, 2014).

Transfer risk: It arises when the private counterparty in a transaction cannot access the market of the necessary currency to fulfil its obligations. It is often caused by the fact that

[6] Basel Accords are a series of three sequential banking regulation agreements (Basel I, II, and III) set by the Basel Committee on Bank Supervision (BCBS). The accords ensure that financial institutions have enough capital on account to absorb unexpected losses. So they give frameworks for the computation of the capital necessary to cover for the aggregate risk (market, credit, operational, legal, etc.) that the banking sector has to face (Valle, 2015).

the government has preferential access to such market and access is restricted to other entities.

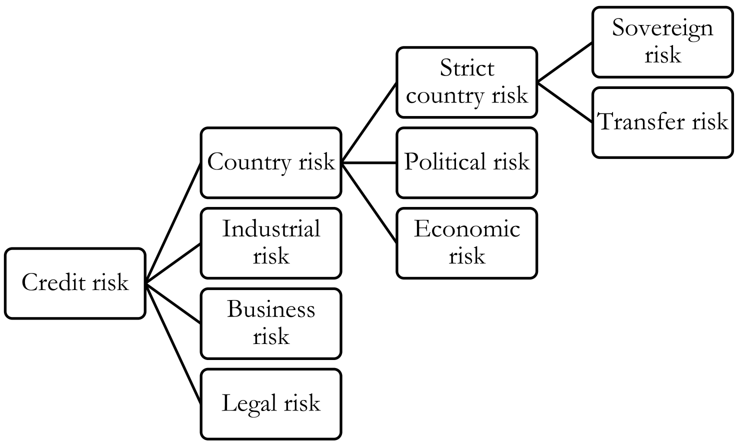

Figure 2 Credit risk overview

2.2 Models of credit risk measurement

Ever since the 60s researchers have proposed many different approaches to credit risk measurement. We can classify them according to the type of information they are based upon (Abinzano, Gonzalez-Urteaga, Muga, & Sanchez, 2020).

2.2.1 Models based on accounting information

Some of the most used models that make use of accounting information to measure credit risk are Altman's Z score (Altman, 1968), Ohlson's O (Ohlson, 1980).

<u>Alman's Z score</u>:

Altman's Z-score predicts the probability of default by means of a linear regression where the different variables are 5 accounting ratios; working capital/total assets, retained earnings/total assets, EBIT[7]/total assets, market value of equity/book value of total liabilities, sales/total assets. The original model that Altman got for the 66 listed companies analysed was:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.999X_5$$

The Z-scores got as a result may be divided into 4 ranges: greater than 3, between 2.7 and 3, between 1.8 and 2.7, and lower than 1.8, being a score greater than 3 a low probability of default and a score lower than 1.8 a high probability of default. Many variations of this model have arisen for publicly and non-publicly traded firms, as well as for manufacturing and non-manufacturing ones, nowadays it is also used to measure default risk under the Basel accords.

[7] Earnings before interest rate and taxes

Ohlson's O:

Ohlson created another linear regression model with 9 variables to measure the level of insolvency of an entity. The 9 variables included were SIZE (the logarithm of total assets/GNP), TLTA (total liabilities/total assets), WCTA (working capital/total assets), CLCA (current liabilities/current assets), NITA (net income/total assets), FUTL (funds provided by operations/total liabilities), INTWO (binary variable with values 1 if net income was negative for the last two years and 0 otherwise), OENEG (binary variable with values 1 if total liabilities exceed total assets and 0 otherwise), and CHIN ([NIt – Niti]/[INItI + INIt-il], where NIt is net income for the most recent period). The model derived was:

$$O = -1.32 - 0.407SIZE + 6.03TLTA - 1.43WCTA + 0.0757CLCA - 2.37NITA - 1.83FUTL + 0.285INTWO - 1.72OENEG - 0.521CHIN$$

In this case, the greater the O-score, the greater the credit risk.

This type of accounting-based models' effectiveness has been criticized because accounting information only reflects past results that may not inform much about the future of the entity (Hillegeist, Keating, Cram, & Lundsted, 2004). Moreover, accounting information is based on the going concern principle of the company, which states that the assets that appear on the company's balance sheet must be valued as if it were to keep going beyond the foreseeable future. Also, firms facing financial hardships have incentives to mask the true situation of the company in their accounts, as many authors in the field of accounting have criticized. Models based on accounting information do not consider the assets' volatility neither; this is very concerning because entities with different volatilities have different probabilities of insolvency, and overlooking this issue conducts to the misleading conclusion that businesses with similar ratings have similar default probabilities too. In reality, the greater the volatility of an entity's assets, the greater its risk of default will be.

2.2.2 Models based on ratings

Rating agencies assess the creditworthiness of corporate bonds and states and provide ratings accordingly. The most well-known rating agencies include Standard & Poor's, Moody's, and Fitch, which are independent companies that use different ratings for both long-term (Table 1: Rating systems of long-term assetsTable 1) and short-term (Table 2) financial assets. A rating expresses the likelihood that the rated party will go into default within a given time horizon. In general, a time horizon of one year or under is considered short term, and anything above that is considered long term. As we can see in Tables 1 and 2, different rating agencies use variations of an alphabetical combination of lowercase and uppercase letters, with either plus or minus signs or numbers added to further fine-tune the rating

Rating systems of long-term assets			
Moody's	S&P	Fitch	Issuer's repayment capacity
Aaa	AAA	AAA	Extremely strong
Aa1	AA+	AA+	Very strong
Aa2	AA	AA	
Aa3	AA-	AA-	
A1	A+	A+	Strong
S	A	A	
A3	A-	A-	
Baa1	BBB+	BBB+	Adequate
Baa2	BBB	BBB	
Baa3	BBB-	BBB-	
Ba1	BB+	BB+	Occasional failure is possible
Ba2	BB	BB	
Ba3	BB-	BB-	
B1	B+	B+	More likelihood of occasional failure
B2	B	B	
B3	B-	B-	
Caa	CCC	CCC	Default is likely
Ca	CC	CC	High default likelihood
C	C	C	Imminent default
	D	D/DD/DDD	Non-payment

Table 1: Rating systems of long-term assets

Rating systems of short-term assets			
Moody's	S&P	Fitch	Issuer's repayment capacity
p-1	A-1	F-1	Very strong
p-2	A-2	F-2	Strong
p-3	A-3	F-3	Adequate
NOT PRIME	B	B	Occasional failure is possible
A-1	C	C	Default is likely
A-2	D	D	Imminent default or non-payment

Table 2 Rating systems of short-term assets

Bond traders are major users of bond ratings. Since they are often subject to investment-grade requirements on their holdings, agencies try to keep these credit ratings relatively stable unless a long-term value decrease is foreseen. The same goes for periods of economic downturn, where the probability of default is expected to decrease in the short run, but to go back to previous levels in the long run. Still, there are companies like Moody's that have introduced methods that do not have rating stability as one of their main objectives – Kamakura or KMV, mentioned above– and rather base their ratings on equity prices and other variables. As a consequence, they are more responsive to market information than the previous (Hull, 2015).

The ratings provided by the different agencies are based on historical data. Historical default probabilities provide useful information for the assessment of credit risk too. Rating agencies, for example, produce data about companies' default experience through time, which is also referred to as unconditional default probability. It is found that for investment grade bonds, the probability of default tends to be an increasing function of time. This is due to the fact that companies are initially rated as creditworthy, and as time goes by, the probability that their financial health will go down increases. The opposite holds for bonds with a poor initial credit rating, whose probability of default tends to decrease over time due to the fact that if the issuer is able to survive the critical period, its financial health must have had improved (Hull, 2015). Conditional default probabilities for a time period t may be computed by means of historical data too, which is referred to as hazard rate or default intensity.

Models based on ratings have their advantages and disadvantages too. On the one hand, they are computed by reliable, specialized agencies with specifically selected methods and data. On the other hand, as aforementioned, rating agencies have a goal of rating stability and take time to modify the ratings of the entities, while they may suffer changes in the meantime. Moreover, different assets with the same rating are supposed to have the same default risk, what is not too accurate. Also, this kind of methods' measurements provide relative comparisons between companies' instead of absolute risk terms.

2.2.3 Models based on market information

Equity prices may be used to estimate default probabilities too. They have arisen as a more up-to-date alternative to credit ratings, which are revised relatively infrequently. Some examples include Merton's model (considered the predecessor of this type of methods), the Black-Scholes-Merton formula, and Moody's KMV model, among others.

Black-Scholes-Merton measurement:

Merton's model (Merton, 1974) views equity as an option on the assets of the company; if the assets are lower than the debt at maturity, the company is likely to default and equity will be less than zero. If on the contrary at maturity the value of the assets of the company exceed the value of the debt, the company should be able to repay its loan and the equity will be given by the difference between the assets and the debt. So, the equity of the company could be viewed as a call option on the value of the assets of the company with a strike price equal to the repayment required on the debt (Hull, 2015) if the option is not exercised, the company defaults. The probability that the firm will not exercise the option cannot be observed, but it can be computed by means of the Black-Scholes formula (Black & Scholes, 1973). This is why some authors propose merging both together for research purposes (Abinzano, Gonzalez-Urteaga, Muga, & Sanchez, 2020), to which they refer as BSM model. The output obtained via the model is sometimes referred to as the distance to default (standard deviation of the asset price with respect to the default option), the lower the distance, the greater the likelihood of default. Many variations of this model have arisen; Moody's KMV and Kamakura, for example make use of this model for one of their services by transforming the default probability it gives into a real-world default probability (Hull, 2015).

The advantages of type of models are that since they are based on the market prices of stocks they take into account the expectations of investors about the future movements of the stocks rather than just past data and that consequently, they also consider their volatilities. However, they are based on some suppositions that may not hold true, like the fact that the assets of a company follow a lognormal distribution.

Models based on risk premium of bonds:

Bond spreads, the difference between the return of an enterprise's liabilities and the return on the same assets risk free, are also used as a proxy for credit risk measurement. Some authors claim that spreads arise as a consequence of factors other than credit risk, and criticize their use as its proxies for that (Elton, Gruber, Agrawal, & Mann, 2001). It is also usually easier to measure and find information about the prices of corporations' stocks than liabilities.

In the case of states in the European Union, credit risk is measured by the differential between the corporate bonds of a member state and those of Germany, considered a risk-free proxy. This approach has been questioned by many authors. Researchers Alonso and Trillo (Alonso & Trillo, 2015), hold that using German bonds as a risk-free benchmark is just conventionality. Increases in spreads are usually linked to increases in credit risk, whereas, in reality, that can be due to two factors: a lower interest rate on the part of Germany (the risk-free proxy) or an increase in the interest rate of the issuer state with credit risk. At the same time, decreases in returns arise as a consequence of price increases usually due to buy pressures in the secondary market (the opposite holds for increasing returns). Hence why, the authors hold that before implementing policies and austerity measures, we should break down the reasons behind the price variations that come from investors' strategies, their degree of information, the uncertainty of the moment and other institutional factors like the policies of the central banks and the ratings of agencies. Other authors, like Barrios, Iversen and Lewandowska (2009) and Bellas, Papaioannou and Petrova (2010) analyse the relation between macroeconomic and financial variables and the sovereign bond spreads too. Blanco et al. (2005) also find that macro-variables, such as interest rates, term structure, equity market returns, and equity market implied volatilities, have a larger immediate impact on credit spreads than CDS spreads. Considering all of this, using CDSs as a proxy for credit risk instead of bond spreads seems sensible, as they might stick more strictly to it.

Another tool used for credit risk assessment are recovery rates. Bonds' recovery rates are usually defined as the price at which the bond trades about 30 days after default as a percent of its face value (Hull, 2015). Recovery rates and default rates follow a negative relationship, a low default rate should imply a high recovery rate, so, it is a useful tool in credit risk management.

CDS spreads:

Among the most widely used derivatives, CDSs are listed as the most liquid and constitute an easy way to trade credit risk because they allow to isolate it and transfer it to a third party with no need to transfer the underlying asset (Blanco, Brennan y Marsh, 2005). Credit default swaps are derivative instruments acting as insurance against an issuer's risk of default, hence why they could be used as a measure of credit risk. Academic literature has widely focused on their spreads as a proxy for credit risk over the past years (Ballester and González-Urteaga (2020), Vashkevich and Basazinew (2013), Broto and Pérez-Quirós (2011), among others).

There are different types of credit default swaps, the simplest one ("vanilla") serves as insurance against a company's risk of default, it is shown in Figure 3. The company that issues bonds is referred to as the reference entity, and its event of default is referred to as credit event. The buyer of the credit default swap obtains the right to sell the bonds issued by the reference entity for their face value to the seller of the credit default swap in case of a credit event. The total face value of the bonds that can be sold is referred to as its notional principal. The buyer of the credit default swap makes payments periodically to the seller in exchange for the insurance until a credit event occurs or until its expiry date comes. The total amount paid by the buyer per year is referred to as the CDS spread.

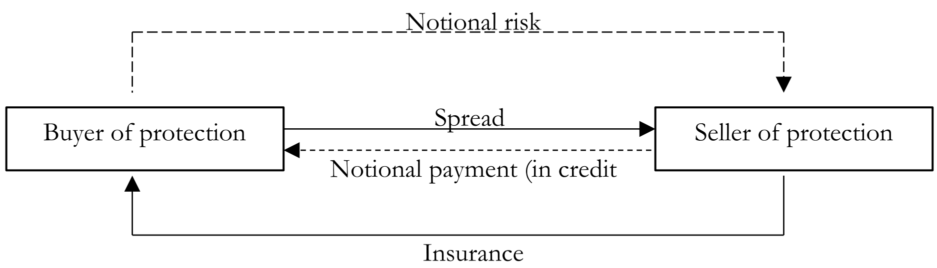

Figure 3 Credit Default Swap

The market for credit default swaps has grown very fast over the years. Ever since its creation in the beginning of the century, the CDS market has changed a lot. According to the ISDA[8]'s Global Credit Default Swaps Market Study, its transaction volume increased rapidly in the first decade and started to decrease after the global financial crisis of 2008. It has remained relatively stable after 2016, but at a higher level than that of the pre-2008 crisis.

Banks are usually the sellers of protection and insurance companies are usually its buyers, but banks also use CDSs to cover exposures to borrowers of other banks. Among the CDS contracts that trade, many companies and countries appear as reference entities too. The most popular, and hence, most liquid contracts are the ones with maturities of five years, but other ones are also traded. CDS contracts also have standardized maturity dates (Norden and Weber, 2009, Ballester, González-Urteaga and Tudela, 2016, Hull, 2015).

As CDS contracts trade with premiums, they give information on the credit risk of the reference entity (let it be a corporation or a country); the more premium asked for, the higher the default probability, and the higher the credit risk.

The CDS-bond basis, defined as the difference between the CDS spread and the bond yield spread, is usually close to zero (Hull, Predescu, & White, 2004), implying that the CDS spread and the bond yield spread are approximately equal. The reasons why the CDS-bond basis differs from zero are most of the times the following: the bond is selling to a price different from par, there is counterparty default risk in the CDS, there is a cheapest-to-deliver bond option in the CDS, the payoff in the CDS does not include accrued interest on the bond that is delivered, the restructuring clause in the CDS contract may lead to a payoff when there is no default, or the LIBOR is greater than the risk-free rate being assumed by the market. This basis was normally positive before the crisis of 2007. When it started, it became negative at times, but that could be due to the lack of liquidity in the markets. After the crisis, the CDS-bond basis has been positive and negative at times, but it has become much smaller in magnitude compared to the pre-crisis (Hull, 2015).

The main disadvantage of CDS spreads is that most companies do not have them, and therefore, they cannot be used to measure their default risk. Also, the fact that states have low default frequencies, makes it difficult to compute their natural default probability

[8] International Swaps and Derivatives Association. It was created in 1985 with the intention to make privately negotiated derivative transactions safer and more efficient and it is made up of more than 800 market participants. In accordance with the official web page, "ISDA's work in three key areas – reducing counterparty credit risk, increasing transparency, and improving the industry's operational infrastructure – show the strong commitment of the Association toward its primary goals; to build robust, stable financial markets and a strong financial regulatory framework".

(Alonso & Trillo, 2015). Still, there are various advantages to using CDS spreads as a proxy for credit risk, those are discussed next.

2.3 Justification of using CDS spreads as the proxy for credit risk

CDSs are widely used as a proxy for credit risk in academia, some examples include Ballester et al. (2020), Coronado et al. (2012), Alonso and Trillo (2015), Trutwein and Schiereck (2011), among others.

Regarding the reasons for using CDSs as a proxy for credit risk, as has been mentioned before, the CDS market is one of the biggest OTC derivatives markets in the world and their value can be found directly in the market. They are highly standardized contracts and more liquid than other risk transfer instruments, facilitating comparisons. CDSs are the most widely used instruments for credit risk transfer and they played a leading role in the previous crises. According to Byström (2005), some authors refer to the CDS market as another agency rating.

They also give information about credit quality in a transversal manner and as time series, and contrary to bond spreads, CDS spreads are not as susceptible to tax effects (Das et al. 2009). Moreover, some studies on the topic show that CDS spreads have more impact on stock returns than bond yield spreads, which is the other widely used proxy to study credit risk transmission.

Also, CDS trading usually[9] implies a far lower funding cost compared with cash bonds, allowing investors to take different positions in the market easily (Longstaff, Mithal, & Neis, 2005).

Lastly, Abinzano, Gonzalez-Urteaga, Muga, and Sanchez (2020), in an analysis of the different alternatives to measure credit risk concluded that contrary to what has been done in the past, the different methods of credit risk measurement mentioned in section 2.2 cannot be used indistinctively, because they lead to different results in terms of risk of non-payment accuracy. They found that the market-based approaches outperform models based on accounting information and credit ratings when it comes to outcome prediction. Among them, CDSs show the most consistent behaviour, being the only to maintain a good fitting capacity over longer time horizons. However, for all scenarios considered, they found that the sample matters, and its characteristics should be considered when choosing a method. Lastly, they suggest investors should consider market based measures, and CDSs specifically, whenever there is data availability, as they are the ones that perform best regardless of the time horizon and type of default. In this case, since the aim is to analyse the credit event of

[9] If counterparties do not require high amounts of collateral.

estates themselves over a quite long time period and data on sovereign CDSs is available, using the spreads of the sovereign CDS as a proxy seems the most suitable choice.

3. LITERATURE REVIEW

In the literature analysing the lead-lag relationship between credit and stock markets, no widespread consensus has been reached. One strand of literature (see Acharya and Johnson, 2007, Calice and Ioannidis, 2012, Narayan, 2015, Vashkevich and Basazinew, 2013) has found that it is the CDS market that leads the stock market, while other authors (see among others Byström, 2005, Ballester and González-Urteaga, 2020, Coronado, Corzo and Lazcano, 2012, Forte and Peña, 2009) find the opposite relationship. Another branch of studies find a bi-directional relationship, that varies across sectors/industries (see Shahzad, Nor, Hammoudeh and Shahbaz, 2017, Narayan, Sharma and Thuraisamy, 2014) or across time/frequency (see, for example, Hilscher, Pollet and Wilson, 2015, Forte and Lovreta, 2015).

Among the studies finding that the CDS market leads the stock market, Acharya and Johnson (2007), for example, tried to identify the existence of insider trading in derivatives markets for the period of January 2001-October 2004 using news reflected in the stock market as a benchmark for public information. They used bid-ask quotes for the most widely traded North American entities' CDS and provided evidence that a permanent information flow form CDS markets to equity markets does exist. Calice and Ioannidis (2012), analysed the dynamics between US and European large and complex financial institutions' equity returns and CDS market indices for the whole period of 2005 and up until November 2008. They found that for all LCFI equity returns and CDS indices are negatively correlated and that the CDS indices are dominant factors driving shocks (the effect was found to be more pronounced for European banks than for US banks). Narayan (2015), moreover, analysed 5-year tenor CDS spread data across 10 different sectors of the US and found that CDS spread returns are the ones that explain the forecast error variance of equity returns too, but his analysis covered a wider time period that included both the pre-crisis and crisis periods from 2004 to 2012. He also concluded that CDS returns and equity returns differ across sectors, implying that riskiness varies across sectors in the US too. The effect of CDS shocks also differs across sectors. In the finance, consumer discretion, materials, and energy sectors CDS shocks explain a large percentage of the variation in equity returns compared to other sectors, with that role maximized during the crisis period. Vashkevich and Basazinew (2013) analysed the period between 2007-2011 (differently to the previous) and concluded that the CDS market leads the stock market too. In this case, their analysis was based on seven East Asian countries' sovereign CDS markets and stock markets, with the aforementioned relationship holding for the whole region.

The literature finding that the stock market is the one leading the CDS market seems to cover wider time periods overall, although there are some exceptions. Some focused on the pre-crisis period, like Byström (2005), who analysed daily closing quotes for European iTraxx CDSs of seven different sectors for the period of 2004-2005. He found that stock returns explain much of the variability in CDS spreads and that information is embedded in stock prices before it is embedded in CDS spreads. Forte and Peña (2009) run a VECM model for a sample of North American and European non-financial firms and for the period of 2001-2003. They found that stocks lead CDS and bonds more often than the other way around. Norden and Weber (2009) examined monthly, weekly and daily data on more than 1000 European reference entities' corporate and bank CDSs for the period 2000-2002 and found that stock returns leads CDS and bond spread variability. They also found that the CDS market is more sensitive to the stock market than the bond market, with the strength of the co-movement increasing the lower the credit quality and the larger the bond issues. Lastly, they found that the CDS market contributes more to price discovery than the bond market, especially in the case of the US compared to the EU.

Other authors found the same relationship as the aforementioned while focusing the analysis mainly on periods of turmoil. Coronado, Corzo and Lazcano (2012) analysed the link between eight European sovereign CDS and stock markets during the period 2007-2012. They found that the stock market leads the CDS market for the period of 2007-2010, but when isolating the years, it is the CDS market that leads the stock market for 2010. This phenomenon was found to be more significant in the countries with high risk spreads. Trutwein and Schiereck (2011) examined the link between credit and equity markets for major financial institutions in the US and increased default risk for the period 2007-2008. They found that both markets become more integrated in times of financial distress and that fast equity price changes lead CDS spread changes.

Another line of research finding the same directional relationship used sample data of both periods of relative tranquillity and periods of financial distress. Fung et al. (2008) analysed the relationships between both markets in the US for the period of 2001-2007 and found that the lead-lag relationship depends on the credit quality of the underlying reference entity. Specifically, they found that the relationship was stronger between the stock and the high-yield CDS markets, while the stock market leads the investment-grade CDS index in the pricing process. Marsh and Wagner (2016) focused their analysis on information transmission in the US for the period 2004-2008 by using pieces of new as a benchmark. They find that equity markets lead the price discovery process following only positive news; one potential explanation for this could be the presence of institutional investors with hedging demands in the CDS market and that the lead-lag relationship for these firms is stronger. These results could also imply that informational asymmetries are present in the market. Ehlers, Gürtler and Olboeter (2010), analysed the lead-lag relationship between both European markets for the period 2004-2009 and for different time frequencies too. They found that information transfers from the stock market to the CDS market during financial turmoil and found a very interesting day-off-the-week-effect on weekly returns, an indication of information inefficiency.

Chan, Zhang and Fung (2008) analysed the dynamic relationship between the stock and sovereign CDS markets of seven Asian countries for the period 2001-2007. Firstly, they found that a strong negative correlation exists between the two. Regarding price discovery processes, they found that CDS markets play a leading role in five of the countries, while the stock market has a feedback effect in two of them and a leading role in the only one.

Ballester and Gonzalez-Urteaga (2020) analyse the period 2004-2016 and find that a connection between both markets exists for Europe and the US, and that it is the stock market returns that anticipate sovereign and banking CDS return, while it is not as clear in the case of financial CDS. Moreover, they find that this relationship is time varying and related to times of financial distress; causality occurs only during bad economic times, although in some Eurozone countries it was present in the post-crisis period.

The last branch of studies finds bi-directional relationships; majority of them carried an analysis including both periods of financial turmoil and relative stability. Hilscher, Pollet and Wilson (2015) find that equity returns lead CDS returns at daily and weekly frequencies for a sample of 783 US firms during 2001-2007, but CDS returns respond more quickly in times of earnings announcements, implying investor inattention.

Forte and Lovreta (2015), using data from 92 European firms during 2002-2008, analysed the relationship between both markets and found that the stock market dominates information transmission in crisis periods, while the CDS markets takes the lead in calm periods. Moreover, they analysed what factors could be behind the observed relationship. They found that the credit risk level of the company has a greater effect on the information share of its stocks than the overall state of the economy. Shazad, Nor, Hammoudeh and

Shahbaz (2017), opted for a sector-oriented approach for the period between 2007 and 2014 and found that there is bi-directional causality in the banking, healthcare, and materials industries of the US. They also find evidence that the lead-lag relationship between the credit and stock markets is time varying for all industries; overall it is the stock market that leads the CDS market in all industries except the utility industry. However, during volatile conditions, CDS spreads also affect the stock market. For the overall market index, it is the CDS market that leads the stock market. Lastly, they also find that macro-economic variables determine the CDS-stock nexuses at the industry level and that their changes are processes faster in stock markets than in CDS markets. In another cross-sectoral study for the period 2004-2012, Narayan, Sharma and Thuraisamy (2014) found the stock market contributes to price discovery in nine of the ten sectors analysed (all except the telecommunications sector) for the US, while CDS spreads do so in only six. In the six sectors in which both markets contribute to price discovery the authors found that it is the stock market that leads the process. The analysis considering the sizes of the different firms concluded that while in most cases both markets contribute to the price discovery process, it is the stock market, again, the one that leads the process. They also found that the crisis period had an effect in the dynamics of both markets' relationship, as the stock market leads the price discovery process, but its influence becomes stronger in the crisis period compared to the pre-crisis period. Moreover, price discovery is size-dependent in both time periods.

All in all, it is worth mentioning that as we can tell, the vast majority of the research carried out has focused on the European and US markets, which is the case of all the studies aforementioned. Little attention has been put into Asian markets that may carry insightful conclusions too. For that reason, in the present study, data on Chinese stock and sovereign CDSs will be analysed in an attempt to contribute to this line of research. Moreover, according to data from the European Commission, China is Europe's main trade partner, accounting for 16.1% of total trade; 22% of total imports come from China, and 10.5% of total exports from the EU belong to them too. Both regions also share good deals of investment with one another, one example that illustrates this topic is the Comprehensive Agreement on Investment (CAI) reached in December 2020, favouring market access between the two. Lastly, some authors have found evidence of spillovers between both regions, especially due to the high trading volume between the two (Zhang, Zhang, & Helwege, 2020). So, considering the increasing main role of the Asian Dragon in global markets, understanding how market and credit risk relate in its case is crucial. On another note, to capture the difference in transmission dynamics that may arise in time periods of different financial nature, a wide period ranging from the 1st of January of 2007 to the 2nd of March of 2021 will be analysed. Like so, the global crisis of 2008, the Eurozone sovereign debt crisis of 2010 and the current sanitary crisis of COVID-19 will be taken into consideration alongside the periods of relative tranquillity falling in between.

4. EMPIRICAL ANALYSIS

4.1 Data description

To carry out the empirical analysis two major datasets have been consulted from the database DataStream. Regarding the CDS market, data of Chinese sovereign CDS spreads from the 1st of January of 2007 up to the 2nd of March of 2021 has been considered. When it comes to the stock market, data from the FTSE China A50 Index[10] has been collected, covering the same relatively long time period in order to enable the analysis of the dynamic relationship between both markets.

The basic statistics of both sovereign CDS spreads and the stock price index have been represented in Table 3 and their daily evolution during the sample period has been plotted in Figure 4. On the one hand, the mean Chinese sovereign CDS spread amounts to 78.62 bps and ranges between 9.00 and 296.70 bps. On the other hand, the mean of the FTSE index is 10,887 bps and it ranges between 5,910.80 and 23,414 bps. All in all, we can observe a high variability for both series. In Figure 4 we can tell that from 2008 on, after the outbreak of the global financial crisis, a rise in credit risk in the form of a rise in sovereign CDS spreads is accompanied by a fall in the equity market, probably due to the respective increase in market risk that characterises periods of increased uncertainty. Similarly, in periods where the CDS spreads go down, in other words, when credit risk decreases, the equity market starts to thrive again. This preliminary analysis shows, consequently, that a negative relationship exists between both series.

	Obs.	Min.	Max.	Mean	Median	S.d.
Sovereign CDS	3,697	9.000	296.70	78.624	73.365	38.772
Stock Index	3,697	5,910.8	23,414	10,887	10,362	3,230

Table 3 Main descriptive statistics of daily stock indices and sovereign CDS spreads

It is also worthwhile to note the different (and opposing) effects that the financial crisis of 2008 and the current sanitary crisis have had in Chinese financial markets. The highest point

[10] In the own words of FTSE Russel "it is a real-time, tradable index of the FTSE Group comprising the largest 50 A Share companies by full market capitalisation of the securities listed on the Shanghai and Shenzhen stock exchanges".

in credit risk, at the same time the lowest point of the value of its stock, happened right after the boom of the global financial crisis, but in the period after 2019, where we are living another crisis that has had very detrimental effects in markets all around the world, Chinese stocks are reaching their second highest value for the whole time period observed, almost reaching the pre-2008-crisis value and credit risk has shown an overall decreasing tendency (although there was a slight peak at the beginning of 2020).

The country has set a great example in its management of the sanitary crisis, with outbreaks being controlled rapidly and efficiently after the first wave, not allowing the incidence of the newly found disease to increase. Still, some macro factors could have also come into place too, for example the injection of money in the economy, like in the case of many other countries including the USA and some EU countries; conducting an analysis on the macroeconomic variables that could affect the lead-lag relationship between the two markets analysed could be a good topic for future research. Another factor to consider for further research is that of the development of cryptocurrencies, where China where taking big steps and what could have a great effect in financial markets too.

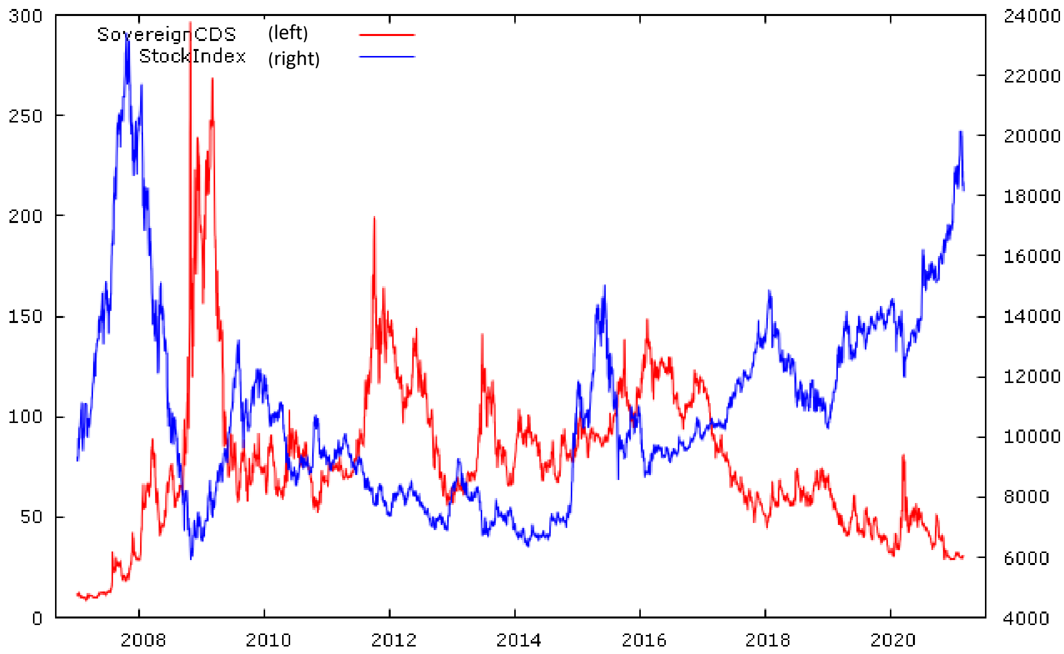

Figure 4 Daily time evolution of the Chinese stock index and sovereign CDS spreads

4.2 Analysis of the correlation

In order to analyse the relative variation between both markets the series have been converted to log-returns. The use of log-returns allows for the normalization of the series, making them comparable. Different tests have been carried out for the converted series. First of all, the Jarque-Bera test gives a p-value lower than 1% both for the sovereign CDS log-returns and for the stock index log-returns, hence, the null hypothesis that the residuals have a normal distribution can be rejected. These results point to non-normal distributions and fat-tails, which are common features of financial series. In order to test for the existence of unit roots, the Augmented Dickey Fuller test and the Philips-Perron test have been carried out. In both cases, the transformed series give a p-value lower than 1%, and so, we can reject the null hypothesis that there is a unit root, confirming stationarity of the log-returns series.

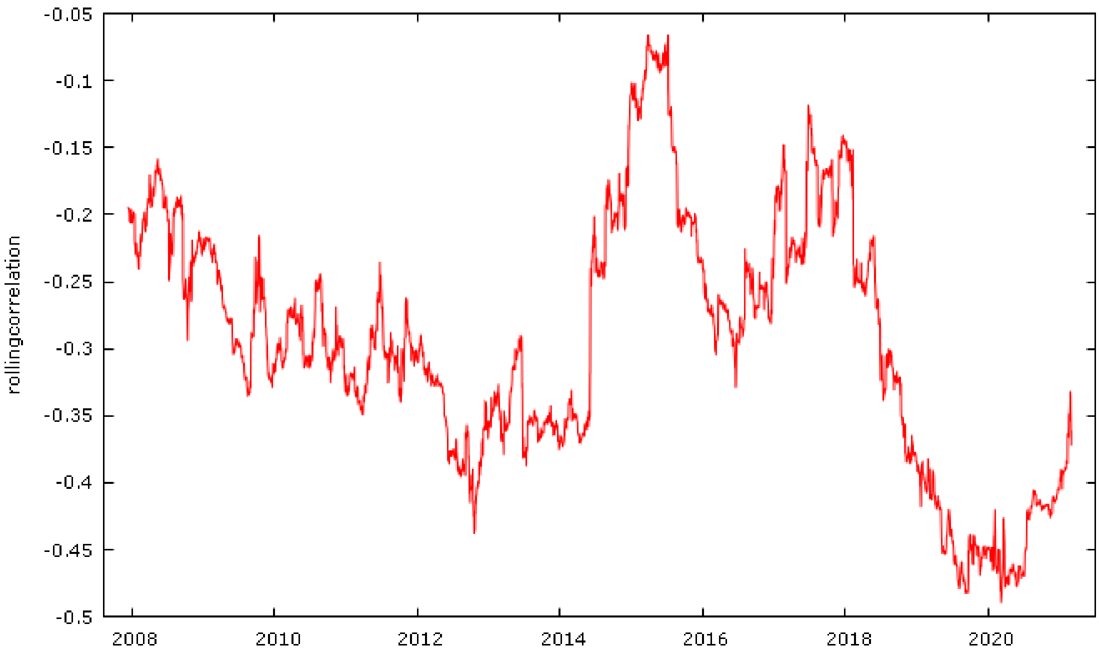

Figure 5 Daily evolution of the correlation coefficients of the Chinese stock index and sovereign CDS using 250-day rolling windows

Figure 5 shows the rolling correlation coefficients for Chinese sovereign CDSs and the FTSE China A50 index using a rolling window of 250 observations. Note that due to the application of rolling windows the first 250 observations were lost, so that the correlation observations begin the 2nd of July of 2007. We observe how, as expected, the correlation between the Chinese CDS and equity markets is always negative. It increased during the period of the global crisis (2008-2009) in absolute value as per usual. In the period corresponding to the European sovereign debt crisis (2010-2013) the correlation remained relatively stable until the beginning of 2012, but it started to increase hereupon and there was a peak in 2013, the highest without considering the COVID-19 era that reached a correlation of 0.44 in absolute terms.

The period of 2012-2013 was characterised by various political and economic changes in China. First of all, the 12th National People's Congress was held; whereby Xi Jinping, the actual president of the nation was elected as the successor of Hu Jintao. This period was also characterised by the slowing of the economy, partly due to the introduction of policies with the objective of moderating growth to a more sustainable rate. At the same time, the real estate bubble that had been inflating from 2005 to 2011 started to deflate, which has been considered as one of the main reasons behind the country's decelerating economic growth in 2012 (Bradsher, 2012). As one of the main trade partners with the European Union, the nation was also affected by the decrease in exports that came along with the European debt crisis; according to the annual report of the International Monetary Fund, the economy mainly felt the spillovers from the European crisis in exports, investment and consumer sentiment. The depreciation of the EUR also led to the appreciation of the CNY, what made its products and services more expensive towards other countries. However, there was enough room to carry out ample policy responses to fight this risk. As a conclusion, we could think that the mixture of all of these factors could have influenced investors' perceptions and expectations on the market, leading to the increasing correlation found in the period. Further research could be carried out by, for example, introducing a proxy for the expectations or investors, which could be measured by analysing the sentiment found in social media comments or publications through artificial intelligence.

After 2013 correlations decreased rapidly, almost reaching a value of 0 towards the end of 2015, corresponding to the period in between crisis as is expected. In 2016 we can find another peak in correlation, although the value reached is 0.33, which is not a very strong correlation but worth to see why the tendency was reverted. This period saw the stock market bubble that had been filling up crash in 2015, whose effects lasted up until 2016. Moreover, news about the existence of risky "shadow" banking and "shadow" credit products in the market arouse and started to spread. Great capital outflows occurred during the period too, and the RMB faced a considerable depreciation, reaching its lowest value in eight years. A new monetary policy framework was also implemented in the process of transitioning to a more market-based approach. All these happenings could be behind the increase in correlations found in the analysis.

Then correlations started to decrease again and the next peak, which is also the highest that can be observed in the series with an absolute value of almost 0.5, came in the period of the

COVID-19 sanitary crisis (2019-2020). After the beginning in 2020 the tendencies seem to have been reversed, with correlation coefficients decreasing.

4.3 Granger causality analysis

The aim of this section will be to analyse the information flow between the two markets to see how they interact with one another. More specifically, we look for evidence pointing to one market anticipating the other. This analysis of the lead-lag relationship between the markets will be carried out following the concept of Granger causality (Granger, 1969).

First of all, a Vector Auto Regressive model (VAR) will be estimated as in Ballester and González-Urteaga, (2020), Coronado, Corzo, and Lazcano (2012), and Shahzad, Nor, Hammoudeh, & Shahbaz (2017):

$$\begin{bmatrix} r_{stock,t} \\ r_{CDS,t} \end{bmatrix} = \begin{bmatrix} \alpha_{stock} \\ \alpha_{CDS} \end{bmatrix} + \sum_{k=1}^{p} \begin{bmatrix} \beta_{stock,stock,k} & \beta_{stock,CDS,k} \\ \beta_{CDS,stock,k} & \beta_{CDS,CDS,k} \end{bmatrix} \begin{bmatrix} r_{stock,t-k} \\ r_{CDS,t-k} \end{bmatrix} + \begin{bmatrix} u_{stock,t} \\ u_{CDS,t} \end{bmatrix}$$

Equation 1 VAR(p) model

where $r_{stock,t}$ and $r_{CDS,t}$ are the FTSE China A50 stock index log-returns and Chinese sovereign CDS log-returns, respectively, and $u_{stock,t}$ and $u_{CDS,t}$ are the error terms of the model.

In order to select the optimal lag length *p* for the VAR model, the Akaike information criterion (AIC) and the Swartz Bayesian criterion (SBC) have been followed. Afterwards, different Granger causality tests (Granger, 1969) have been carried out for the different subperiods: the whole series, the period prior to the global financial crisis, the one of the global financial crisis, the sovereign debt crisis, the period between crises and the current sanitary crisis of COVID-19. For this, the null hypotheses stating that Chinese sovereign CDS log-returns do not explain the variability in the Chinese stock price index and that stock price index log-returns do not explain the variability in sovereign CDSs have been tested, which is the equivalent of testing whether sovereign CDSs do not granger cause the stock price index and vice versa. Being able to reject these null hypotheses would mean that there is enough information to conclude that past values of the series includes information that could help predict future values of the other. This is carried out by imposing the restriction that the coefficients (βs) take the value 0; more specifically, we test whether the sovereign CDS market granger causes the stock market if $\beta_{stock,CDS,k} = 0$, and whether the stock market granger caused the sovereign CDS market if $\beta_{CDS,stock,k} = 0$. The resulting p-values are shown in table 4.

Full sample Jan 2007 – Mar 2020		Pre-crisis Jan 2007 – June 2007		Global crisis Jul 2007 – Dec 2009		Eurozone sovereign debt crisis Jan 2010 – Dec 2013		In between crises Jan 2014 – Nov 2019		COVID-19 crisis Dec 2019 – Mar 2020	
CDS	FTSE	CDS	FTSE	CDS	FTSE	CDS	FTSE	CDS	FTSE	CDS	FTSE
0.007	0.046	0.165	0.256	0.023	0.199	0.080	0.000	0.446	0.341	0.248	0.003

Table 4 Granger causality test results

Overall, the granger causality between the series seems to be unstable and time varying. The test for the full sample showed that bidirectional granger causality exists between the two markets at a 95% level of significance, with both markets granger causing one another, although it seems that the CDS market holds more of a leading role than the stock market. This is consistent with the results of Chan, Zhang and Fung (2008), who also found that in the case of China a bidirectional causality exists between the stock and the sovereign CDS markets.

If we dive further in, we find that in periods of tranquillity, for both the pre-crisis and the in-between crisis periods, no granger causality can be found, which is consistent with the results of the rolling correlation analysis carried out earlier, where low levels of correlation were observed in periods of tranquillity. Similarly, granger causality can be found in periods of financial turmoil, with its direction changing over time. In the period of the global financial crisis, the sovereign CDS market appears to lead the stock market at a 5% level of significance. Later, in the European sovereign debt crisis, the stock market leads the CDS market. Finally, for the period of the COVID-19 crisis it is the stock market the one that leads the CDS market too. Note that this could highlight the fact that the different nature of the different crises does affect the lead-lag relationship between both markets; the actual sanitary crisis of COVID-19 and the previous financial crises have very different origins, although all of them had huge impacts in financial markets.

All in all, we could infer, that the lead-lag relationship depends on the economic cycle, but information transmission processes definitely exist between the two markets in bad economic times.

Apart from the analysis by subperiods, the VAR model has been estimated using 250-day windows to identify the dynamics of the causal relationship between the CDS market and the stock market. This approach follows the authors Kollias, Mylonidis, and Paleologou (2012) and Ballester and González-Urteaga (2020), who approximate the number of trading days per year by using a rolling window of 250 days. Like this, two causality test series are obtained for the full period (taking out the 249 first days of the sample) and the conventional static granger causality analysis is updated allowing to study whether the causality relationship varies over time.

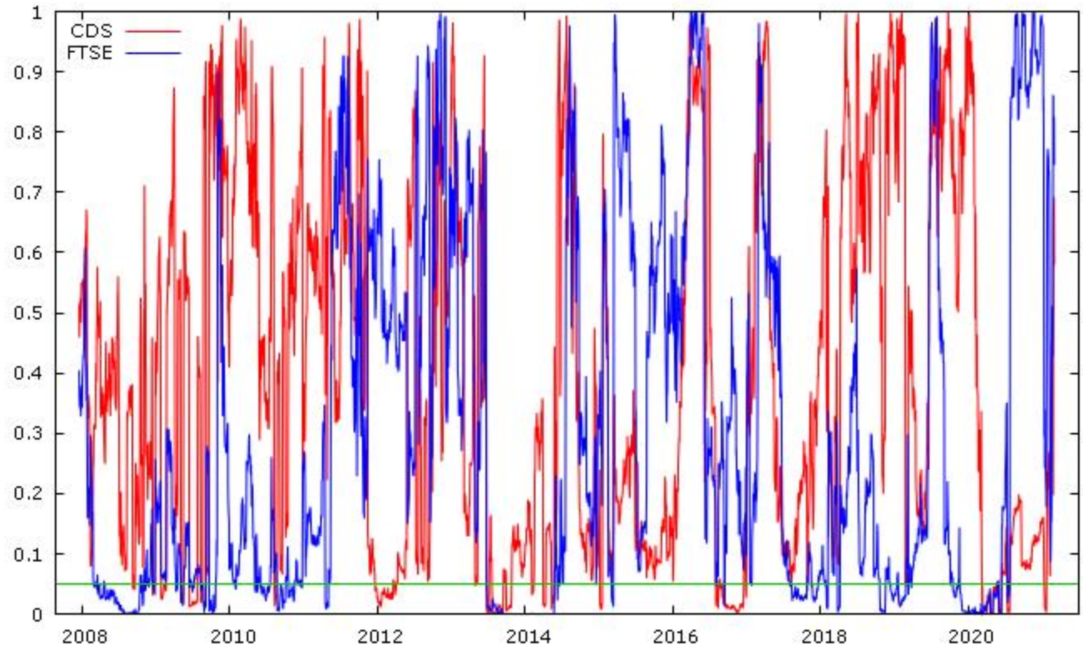

Figure 6 P-values resulting from the rolling Granger causality analysis

Figure 6 shows the p-values resulting from the computation of the rolling VAR model and the subsequent Granger causality tests, with the green line representing a level of significance of 5% for either the CDS market granger causing the stock market (in red) or the stock market granger causing the CDS market (in blue). The results show some differences compared to the analysis via subperiods. In the analysis through rolling windows, overall, the causalities between both markets are unstable and vary over time too, but the stock market appears to prevail as the leading market for the whole sample. We can see that this holds for the period of the global financial crisis (Jul 2007 – Dec 2009), whereas the analysis through subperiods showed the opposite direction of the causality. Moreover, in the period in-between crises (Jan 2014 – Nov 2019) no significant causality was found earlier, here, however, we can find some peaks in the causality in both directions; still, it does appear that causality dynamics are exacerbated during periods of financial distress, as it was found earlier. For the rest of the sample, the results found earlier appear to hold.

We go further in this analysis and like Ballester and González-Urteaga (2020) we make use of the two series of p-values computed through the rolling VAR model to identify three possible transmission mechanisms present between the two markets observed: the CDS market leads the stock market, the stock market leads the CDS market, there exists a bidirectional causality between the CDS and the stock markets. For this, the number of rolling windows (in percentage terms) in which the different causalities can be observed has been computed. Then, the percentages for the full sample period and the different subperiods have been calculated. Like this, the traditional Granger causality test giving back a static analysis for the whole sample period is improved, further allowing to analyse how the relationship dynamics vary over time. The results are shown in Table 5.

Full sample Jan 2007 – Mar 2020			Global crisis Jul 2007 – Dec 2009			Eurozone sovereign debt crisis Jan 2010 – Dec 2013			In between crises Jan 2014 – Nov 2019			COVID-19 crisis Dec 2019 – Mar 2020		
CDS	FTSE	BI	CDS	FTSE	BI	CDS	FTSE	BI	CDS	FTSE	BI	CDS	FTSE	BI
13,3 %	28,4 %	6,3 %	15,4 %	47,4 %	7,9 %	14,6 %	24,5 %	6,8 %	9,0 %	21,2 %	2,1 %	26,0 %	43,7 %	22,0 %

Table 5 Granger causality test results count

The results of this analysis are consistent with those of the analysis of the rolling Granger causality p-values (consider the table has been computed from those values). So, Table 5 shows, that the dynamics between the two markets are exacerbated in periods of financial distress too, where the percentages of times granger causality is observed become higher. Moreover, again, the transmission dynamics appear to be heterogeneous over time. Overall, the period in which the CDS market appears to lead price discovery in more windows is that of the COVID-19 crisis and the period in which the stock market appears to lead price discovery in more windows is that of the global financial crisis, followed very closely by the period of the COVID-19 crisis. Bidirectional price discovery mechanisms tend to appear much less for all subperiods in general, except for that of the COVID-19 crisis. It is interesting to note that in the recent sanitary crisis not only the number of causalities in which the CDS market and the stock market lead price discovery have increased, but the number of bidirectional price discovery mechanisms has seen its greatest increase, showing the maximum value for the different time periods analysed. Compared to the previous two financial crises, the number of 250-day rolling windows in percentage terms in which bi-directional Granger causality is found has been more than doubled; this could be related to the different nature of the crises analysed (financial crises versus sanitary crisis).

All in all, we may confirm that the dynamics between the two markets are time varying and dependent of the economic cycle, with increased transmission mechanisms in times of financial distress.

5. CONCLUSIONS

In the present study a VAR model has been used to analyse the lead-lag relationship between the CDS and stock markets. Given the fact that previous research on this specific topic is not numerous, and is especially limited with regards to Asian markets, daily data on Chinese sovereign CDS spreads and stock prices between 2007-2020 have been considered, whose increasingly important role and interlinkedness in global markets draws us to learn further about its risk transmission mechanics. A long time horizon covered by the data allows for a better analysis of the impacts that crises of different natures, such as the global financial crisis or the COVID-19 crisis might have on the information transmission between the markets of interest. By understanding how the different crises are formed and the way they are transmitted between markets future financial distress could be faced and managed in a more efficient manner.

The results for the analysis show that Granger causality varies over time and depends on the economic cycle. When considering the whole time sample, it appears that both markets Granger cause one another. In times of stability no causal relation can be found from either of the markets to the other. For the different periods of crisis, however, the connection between the markets becomes evident and besides, the direction of the causality varies. For the period of the global financial crisis the CDS market appears to lead the stock market, while for the period of the sovereign debt crisis and for that of the COVID-19 era the stock market has taken the lead. The analysis with the 250-day rolling windows showed that the dynamics between the two markets are exacerbated in periods of financial distress too. However, the dynamic analysis reveals some different results that deserve to be highlighted. During the global financial crisis, the stock market appears to prevail as the leading market; moreover, this happens during the beginning of the subperiod, which coincides with the most intense period of the crisis. We also observe that bidirectional causality appeared much less than the other two unidirectional for all subperiods in general, except for that of the COVID-19 crisis. It is precisely during the first wave of the health crisis that the highest percentage associated with bidirectionality is observed, probably highlighting the different nature of the crises analysed.

All in all, we might conclude that information transmission mechanisms are present between the Chinese CDS market and the stock market. These findings could be useful to understand how risk is transmitted between the two markets; correlations and price discovery processes could guide investors and policy makers when facing decisions involving the management of credit derivatives. Moreover, this research highlights the importance of considering the economic cycle being experienced when designing different strategies. For future research it would be interesting to add more macroeconomic variables into the analysis, such as the money supply (M2 in this particular case), that could have taken part in the results found, and variables measuring the overall sentiment of the market and investors, for example, it would be interesting to use comments and publications found on social media (WeChat) as a proxy and assigning feelings to different words found within via Artificial Intelligence.

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