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Sovereign CDS-bond basis in Eurozone countries: an empirical analysis of equilibrium during the COVID-19 pandemic

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ABSTRACT

I analyze the theoretical no-arbitrage condition stating that the difference between CDS spreads and bond yields over a risk-free benchmark should be zero in equilibrium, as they depend on the same default probability. The study displays the main characteristics of CDS contracts and then uses the PECS (Par Equivalent CDS Spread) method to measure the CDS-bond basis before and after the COVID-19 pandemic outbreak in 2020. Then, a multiple regression analysis is conducted in order to identify the main factors that contributed to explaining the behavior of the basis. Drivers as liquidity, funding frictions, exchange rates are considered, as well as the impact of the ECB's PEPP. The focus of this study is on a sample of "peripheral" and "core" Eurozone countries, as one of the objectives is to show how heterogeneously the pandemic impacted across different groups of countries.

CONTENTS

Introduction

In this thesis I analyze the theoretical no-arbitrage condition stating that the difference between CDS spreads and bond spreads above the risk-free rate should be zero in equilibrium, measuring how the recent COVID-19 crisis impacted the relative pricing of credit risk in Eurozone sovereign debt markets.

The novel Coronavirus disease caused by the SARS-COV-2 virus provoked one of the most widely spread pandemic of modern times. Originated in Wuhan, the virus peaked in China on February 12th, 2020, and since then has spread worldwide. As of May 2021, according to data from the John Hopkins University[1], since late 2019, the disease has caused more than 160 million infections and almost 3.5 million fatalities globally. Moreover, the emergence of new “variants of concern” (especially the ones originating from the UK and South Africa (VOCs) starting from late 2020 contributed to amplify the crisis, as they gave the disease about a 60% higher ability of transmission[2].

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[1] https://coronavirus.jhu.edu/map.html

[2] https://www.ecdc.europa.eu/en/publications-data/covid-19-infographic-mutations-current-variants-concern

After the World Health Organization declared COVID-19 as a pandemic on March 11th, 2020, several countries began to adopt restrictive measures to face the sanitary emergency such as traveling limits and night curfew.

The restrictions adopted by governments have had a strong impact on the European economy (Figure 1): according to Eurostat calculations[3], the average GDP of the European Union countries shrunk by 6.1% with respect to 2019, with the most severely hit countries, such as Spain, Italy and Greece, having a contraction of 10.8%, 8.9% and 8.2% respectively.

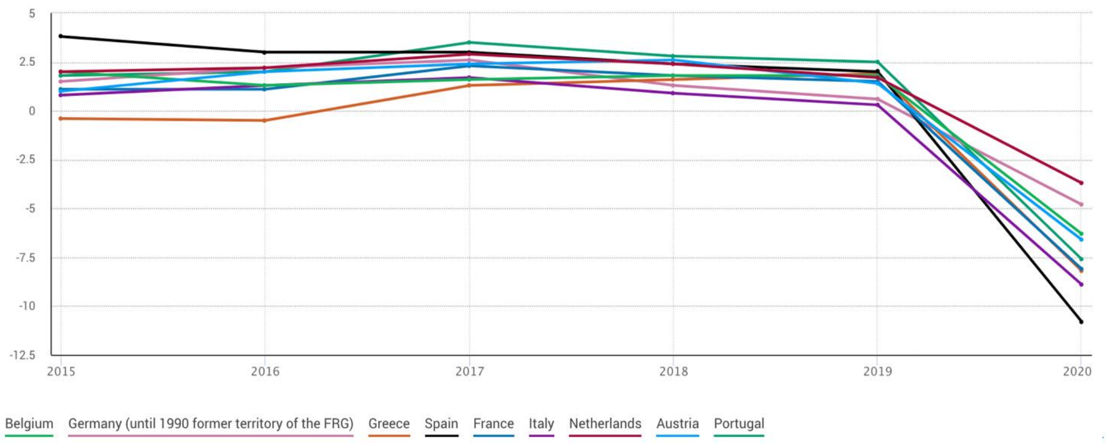

Figure 1: Eurozone %YoY GDP (from 2015 to 2020). Source: Eurostat.

The decline in GDP was also reflected in a deterioration in public finances of several European countries, that increased their debt levels to threatening values since the beginning of the pandemic: the combination of an increase of the stock of sovereign debt and a decline in GDP made the debt to GDP ratio skyrocket for Greece, Italy and Portugal, with an increase from 180.7% to 205.6% from Q1 to Q4 of 2020 for Greece (137.8 to 155.8 for Italy and 119.2 to 133.6 for Portugal), and to exceed 90% on an European average basis.

The deterioration in public finances and the instability in debt markets lead to a strong response by the European Central Bank: starting from March 2020, the PEPP (Pandemic

3 https://ec.europa.eu/eurostat/databrowser/view/NAMA_10_GDP__custom_78848/bookmark/bar?lang=en&bookmarkId=7681260e-2f75-4cd7-a153-02fc89543f2c

Emergency Purchase Programme), which is defined as "a non-standard monetary policy measure […] to counter the serious risks to the monetary policy transmission mechanism and the outlook for the euro area posed by the coronavirus (COVID-19) outbreak"[4], was implemented. This measure represented a massive response compared to the previous Asset Purchase Programme (APP) which started in 2014 to counter deflation: in April 2021, the ECB bought 20 billion euros of sovereign bonds from the 19-countries currency bloc under the APP, while it bought 80 billion under the PEPP. However, while the pandemic can be considered as a symmetric shock across Eurozone countries, recent studies[5] have found an asymmetric impact of the PEPP announcements and implementations both in bond and Credit Default Swaps (CDS) markets. More interesting research regards the fact that this measure certainly contributed in easening liquidity and interest rates tensions in the countries with the highest debt/GDP but could not have avoided the raise in perceived default risk in the same countries.

Considering the scenario described above, this work studies how the pandemic impacted on credit risk in sovereign debt markets. More specifically, it compares the relative pricing of sovereign CDS, and government bonds issued by the same country, to test whether the theoretical no-arbitrage relation, stating that the two prices should be equal (as they price the same credit risk) held up or if it was violated. The thesis considers a sample of 9 EMU countries and the period January 2015 to April 2021. The aim of this work is to identify the key drivers of the movement of the sovereign credit risk pricing and the difference in prices between CDS and bond spreads, called "CDS-bond basis", and to compare this behavior to past crises. To explain the movements of the basis, many factors will be considered, in addition to the ECB's PEPP: short selling frictions, liquidity frictions, exchange rate uncertainty will also be included as possible drivers for the basis.

Chapter 1 focuses on CDS: it illustrates what a CDS is, how it is used and how it is priced.

Chapter 2 discusses the theoretical relation that links CDS and bonds, and how and when this relation has been violated in recent past crises. It also describes the two methodologies used in the analysis to compute the CDS-bond basis.

Chapter 3 contains the results of the empirical analysis that contribute to previous literature in this field.

[4] https://www.ecb.europa.eu/mopo/implement/pepp/html/index.en.html

[5] See Carnazza & Liberati (2021) among all.

Overall, the results suggest that most of the variables considered were significant in explaining the movements of the basis, and their impact were consistent with the initial expectations. Moreover, the ECB played a role in the divergence of the bases of core and peripheral countries.

Chapter 1

Credit Default Swaps

Introducing Credit Default Swaps and how they are priced is crucial in order to fully understand the dynamics that link them to bond markets. It will also be useful to describe the PECS methodology, used in this thesis to compare CDS and bond spreads. This first chapter starts with a brief historical introduction on credit derivatives, moving on to the world of CDS, their features, their classification and the main pricing methods proposed in the literature and used in this work.

1.1 Introduction to credit derivatives

Credit derivatives are "contracts where the payoff depends on the creditworthiness of one or more companies or countries"[6]. They are Over-The-Counter derivatives contracts in

[6] Hull J.C., (2015). Option, futures and other derivatives (ninth edition).

which the underlying asset is a bond, issued by a government or a company, and their payoff depends on whether the issuer defaults within a certain maturity or not.

The growth of the credit derivatives market, since their introduction in the early 90s, has been noticeable, with the outstanding notional principal going from about 800 billion in the 2000s to almost 60 trillion before the subprime crisis in 2008. A survey by ISDA (International Swap and Derivatives Association) dated 2007, showed how significant the credit derivatives market was: estimated at midyear at 45.46 trillion dollars, it outsized the US corporate bond market, the US Treasury market and the US equity market combined by more than 2 times[7].

Before introducing the mechanics of the main credit derivatives contracts (in this thesis the focus is on Credit Default Swaps, which are described in the next paragraph), it is necessary to understand what drove this exponential growth.

The success of credit derivatives is traceable to one main reason: for the first time, they allowed banks and financial institutions to trade the credit risk originated from a loan in the same way as market risk, in other words, to transfer credit risk from their balance sheets to the market. Credit risk has always been an issue for banks, and they have always been reluctant to keep loans in their assets: firstly, because by keeping the loan, the bank bears the total credit risk of the borrower. Meaning that, once the loan is made, the bank must anticipate that the borrower won't default before the maturity, causing a loss in its balance sheet. Secondly, because of the regulatory framework in which banks operate: since 1988, the Basel Committee on Banking Supervision[8], set the amount of capital a bank must have in relation to the loans it can grant (Basel Accord). Basel II (2007) and Basel III (2013) reinforced the capital requirement for banks, linking them respectively to the rating of the issuer and to the RWA[9]. Credit derivatives, in this framework, represent convenient instruments, because banks can use them to transfer the credit risk of a loan to another market participant, unlocking new loan capacity.

Moreover, there are some more "practical" and contractual reasons for which credit derivatives, outsized the bond market[10], before the crisis of 2008. A relevant one is that,

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[7] These estimations are based on the Security Industry and Financial Markets Association Research Quarterly of August 2007.

[8] "The BCBS is the primary global standard setter for the prudential regulation of banks and provides a forum for cooperation on banking supervisory matters. Its mandate is to strengthen the regulation, supervision and practices of banks worldwide with the purpose of enhancing financial stability" (Bank of International Settlement definition).

[9] Risk-Weighted Assets.

[10] O'Kane, Modelling single-name and multi-name credit derivatives, 2012.

using credit derivatives, it is way easier to go short on credit risk than using bonds[11]. By simply taking a long position on a credit derivative contract, a bank is actually going short on credit risk, either for the purpose of hedging an existing credit position or just for speculative reasons.

Another factor is that most of these contracts are unfunded, meaning that entering in a credit derivative requires no initial payment. What is called the notional principal, in fact, is never exchanged between the two parties, and it is only used to compute the cash flows of the contract.

These contractual reasons are fundamental for the objective of this thesis, because the contractual differences between credit derivatives and bonds can be explanatory of the basis.

The world of credit derivatives experienced great success from the end of the last century to the subprime crisis (as described in paragraph 1.1). However, many articles studied their role in fostering the crisis, concentrating credit risk in the hands of few big market participants rather than dispersing it. An interesting article by Alnassar et al. (2014) concluded that the misuse of credit derivatives and of CDS exacerbated the 2008 crisis, bringing the financial giant AIG[12], that had sold credit derivatives for a total exposure of $64 billion, near the collapse. The bad reputation acquired during the crisis dramatically downsized the market: more recent data from the Bank of International Settlements estimated the outstanding notional amount of credit derivatives to be around 8,4 and 8,1 trillion of US dollars in the first and second half of 2019 and slightly more than 9 trillion in the first half of 2020.

There are three factors, pointed out by market observers, that can be dangerous and that contributed to the crisis[13]. The first argument states that, since these contracts are traded over the counter, there is a general lack of transparency, and that some participants manipulated the market in order to make some entities appear less creditworthy than they actually were. The second argument is that a few market participants built huge positions, condensing all the credit risk rather than dispersing it. Institutions, such as Bear Sterns and Lehman Brothers, worsened the confidence in the financial system, especially after

[11] Contractual differences between CDs and bonds are one of the main drivers of this work. They will be deeply discussed in Chapter 2.

[12] American International Group: in 2008 it was one of the largest insurance companies in the world.

[13] Stulz (2010).

the collapse of Lehman on September 15th, 2008. The third “dangerous” feature of CDs and CDS is the “domino effect” they provoked across all the other financial institutions. In fact, since Lehman, Bear Sterns and AIG were also some of the most important reference entities in the CDS markets at the time, their difficulties spilled over the global financial system, causing trouble in the whole banking sector and thus in the whole economy[14].

The slow and steady decline of the notional amounts was also due to the rules introduced by regulatory authorities in response to the crisis. As pointed out by Aldasoro et. al (2018) the introduction and rise of Central Counterparty Clearing Houses (CCPs)[15] contributed to this decline after the crisis.
Specifically, regarding CDS, which are the focus of this work, the Small Bang Protocol introduced in 2009 aimed for a standardization of CDS contract, to increase transparency and ease of trades.

1.2 Credit derivatives classification

Classifying the world of credit derivatives is a hard task, either because they are traded over the counter or because they are composed by a wide range of contracts with different features shaped to meet the trader’s needs.
Nevertheless, credit derivatives can be macro-classified in “single-name”, if the underlying asset is a single company or a single country (single-name CDS are the most popular and liquid of this category), or “multi-name”, when the underlying is a basket of governments or companies (examples are Synthetic CDOs and CDS indices).
As shown in the first Panel of Table 1, in the last 2 years the notional amounts outstanding were almost equally divided between single-name and multi-name credit derivatives, with the latter being slightly higher. The second Panel, instead, shows how the notional amounts of credit defaults swaps outstanding are spread by location of counterparty. What

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[14] Hellman et al (2000).

[15] A CCP is an entity that helps facilitate trading of derivatives: operated by a country’s major banks and working as an intermediary between buyers and sellers, it reduces counterparty, operational, settlement, market, legal and default risk for traders (Investopedia) https://www.investopedia.com/terms/c/ccph.asp

we can note is that, while during the pre-subprime crisis they were extremely popular in the US, nowadays a considerable portion of the market shifted to developed European countries, that are the focus of this work.

Global OTC derivatives market

In billions of US dollars

	Notional amounts outstanding				Gross market value			
	H1 2019	H2 2019	H1 2020	H2 2020	H1 2019	H2 2019	H1 2020	H2 2020
Credit derivatives	**8,418**	**8,119**	**9,050**	**8,649**	**235**	**222**	**200**	**219**
Credit default swaps	**7,809**	**7,578**	**8,809**	**8,359**	**214**	**199**	**185**	**202**
By instrument								
Single-name instruments	3,579	3,480	3,617	3,484	101	99	92	77
Multi-name instruments	4,229	4,098	5,192	4,876	112	101	93	125

Credit default swaps, by location of counterparty

Notional amounts outstanding, in billions of US dollars

H2 2020	All locations	Home country	Abroad						
			Total	US	European developed countries	Japan	Other Asian countries	Latin America	All other countries
Total	**8,359**	**1,978**	**6,154**	**1,816**	**3,668**	**75**	**76**	**277**	**242**
Bought (gross basis)	4,974	1,126	3,721	1,009	2,297	71	57	154	133
Sold (gross basis)	4,646	1,078	3,446	961	2,155	53	36	125	115
With reporting dealers	**1,261**	**226**	**1,012**	**155**	**784**	**49**	**16**	**2**	**6**
Bought (gross basis)	1,269	228	1,022	155	789	54	15	2	6
Sold (gross basis)	1,252	225	1,002	154	778	44	18	1	7
With non-reporters	**7,099**	**1,751**	**5,142**	**1,662**	**2,884**	**25**	**60**	**275**	**235**
Bought (gross basis)	3,705	898	2,698	854	1,508	16	41	152	127
Sold (gross basis)	3,394	854	2,444	807	1,377	9	19	124	108

Table 1: Panel 1: The size and composition of credit derivatives market in 2019 and 2020[16]; Panel 2: the size of CDS market, by location of counterparty. Source: Bank for International Settlement (BIS) statistics.

1.3 CDS mechanics

This paragraph discusses in depth the characteristics and mechanics of a CDS contract. This part is included in the thesis because it will be useful in the next chapter, where the model used in this work (the PECS) to compare CDS and bonds is explained.

[16] https://stats.bis.org/statx/srs/table/d5.2?f=pdf

The CDS was invented in the mid-1990s by a young Cambridge University mathematics graduate, Blythe Masters, who was then hired by J.P. Morgan Chase Bank in New York. The idea behind this contract is simple: it is, in fact, a sort of insurance on credit risk of an entity.

In the single-name standard CDS, the purpose of the contract is to protect one party (called the protection buyer) from the loss from par of some specified bonds or loans after the credit event[17] of the issuer. The bonds covered by the contract are called delivered obligations and the issuer is called reference entity, while the other party in the contract (the one that covers the losses of the buyer in case of the credit event) is called the protection seller.

As the name suggests, CDS are swaps contracts: it means that the initial value of the contract is zero, and there are no initial costs while entering the contract.

The general mechanics of a CDS contract is shown in Figure 2.

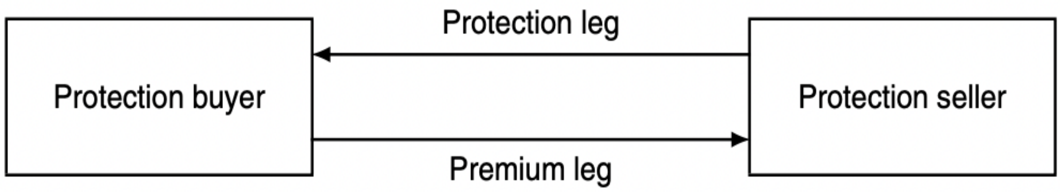

Figure 2: general mechanics of a CDS contract. Source: O'Kane, D., 2008. Modelling single-name and multi-name credit derivatives.

Similarly to IRS[18] contracts, there are two cash flows exchanged by the parties: the protection leg and the premium leg. The two next paragraphs are specifically dedicated to the protection leg and the premium leg. Even if this is not explicitly the aim of this thesis, a deep understanding of these mechanics is crucial to develop a significant model for the pricing of CDS, which will be used to convert market bond spreads for the comparison with CDS spreads. In fact, the cash flows exchanged by the parties in a CDS are the reason why these contracts can be compared to bonds.

[17] The credit event does not necessarily have to be a default: see paragraph 1.3.3 for a more detailed explanation.
[18] Interest Rate Swaps.

1.3.1 The protection leg

The protection leg is the contingent amount that the protection seller must pay to the protection buyer if the credit event occurs before the maturity of the contract[19].

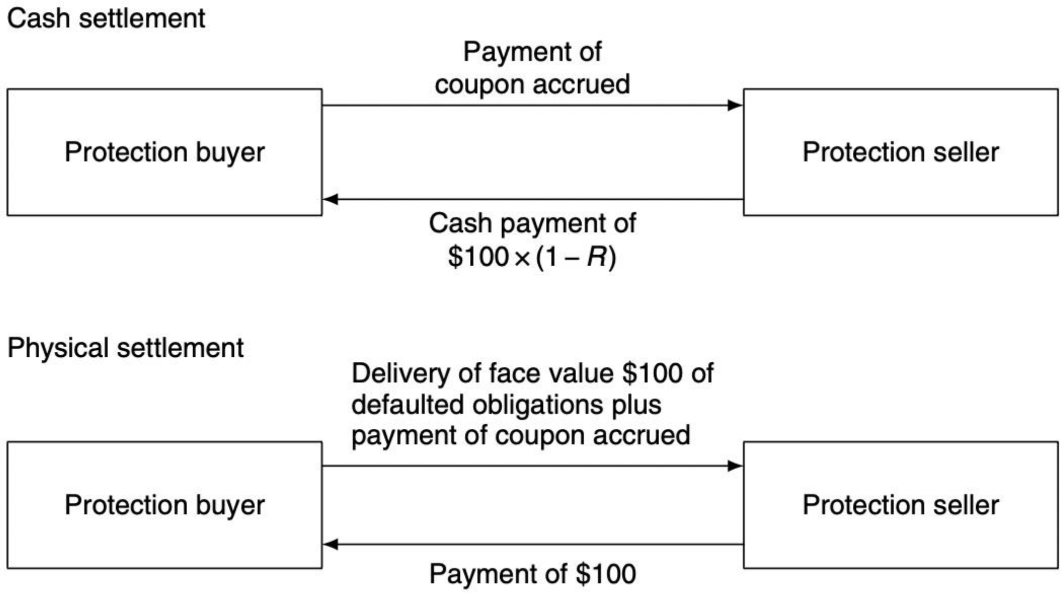

Figure 3: settlement of a CDS in case of default. Source: O'Kane, D., 2008. Modelling single-name and multi-name credit derivatives.

Figure 3 shows the two possible ways in which the contract can be settled. In the first way, when the credit event occurs, the protection seller pays the protection buyer a cash amount equal to the face value of the bond multiplied by (1-R[20]). This amount corresponds to the loss in value incurred by the deliverable obligation after the credit event.

In this first case, the CDS is said to be cash settled.

In the second case, when the credit event occurs, the protection seller pays the buyer the whole face value of the bond (in the example showed, 100$), while the buyer delivers the defaulted obligations to the seller.

[19] More precisely, the protection starts from the effective date (the calendar date after the trade), until the scheduled termination date.

[20] R is the Recovery Rate of the bond: it is the value of the bond after the credit event. This parameter has a crucial role in determining the CDS spread, and its estimation will be discussed later in this work.

1.3.2 The premium leg

The premium leg is the amount that the protection buyer must pay to the protection seller to cover the losses from a default of the issuer of the reference obligation.
More specifically, it consists in a series of payments typically made quarterly, according to an Actual 360 basis. These payments are set as a small percentage of the notional principal, and the percentage that the buyer must pay to fulfil his contractual obligations is called premium or spread[21], and they are often indicated in basis points (100 bps = 1%). Since the introduction of the small-bang protocol in 2009 (introduced in paragraph 1.1), that aimed at a standardization of CDS markets, the premiums consist in an upfront payment, and a fixed periodic amount set a-priori in relation to the creditworthiness of the issuer. For the European sovereign CDS, the premiums are fixed at 25 basis points for the entities with tighter spreads and 100bps for the ones with higher spreads[22].
Despite these technical trading features, the combination of the upfront payments and the fixed coupon rates lead to a CDS premium that is like the previous contracts (Fontana and Scheicher, 2016), and the floating premiums are still observable in the market.

The last, but not least interesting[23] feature regarding the premium leg is how it works when a default occurs. In this case, even if the payments usually occur on fixed dates, the contract expires before the maturity and the protection buyer must pay the seller the fraction of the premium accrued between the last payment day and the default date. This accrued coupon is paid by the buyer both in cash settled and physical settled contracts. This feature matters in the correct valuation of the CDS.

[21] The use of the word "spread" for the payments of the buyer is relevant and will be discussed in Chapter 2.
[22] The protocol also introduced the fixed coupon dates on March 20th, June 20th, September 20th, and December 20th.
[23] Other contract characteristics are intentionally excluded as they don't directly impact the valuation model this work uses.

1.3.3 The credit event

In the world of credit derivatives, the word "default" is often used to refer to the credit event. In reality, default is a sufficient but not necessary condition to trigger the protection leg. Other conditions commonly used as credit events are:

- Bankruptcy: the issuer becomes insolvent and can no longer repay its debts.
- Failure to pay: the issuer fails to make due payments, even after a grace period;
- Obligation acceleration: the issuer must pay its obligations earlier than it would have been.
- Repudiation/moratorium: a reference or government authority repudiate the validity of the issuer's obligations.
- Restructuring: the issuer has its obligation schedule modified to face financial distress and liquidity and make its debt more manageable overall[24].

The first 4 credit events proposed are called "hard" because, in these cases, all the obligations suddenly become payable and have the same price, which is the recovery price of the bonds.
Restructuring, instead, is a "soft" credit event, meaning that when a restructuring occurs, the obligations of the issuer continue trading with a term structure of prices (debt with short maturity will have an increase in price with respect to long term debt).

Considering that the focus of this work is on developed European sovereign issuers, the first 4 credit events are highly unlikely: while bankruptcy and failure to pay are virtually impossible in the sample considered, obligation acceleration and repudiation/moratorium are often used as trigger events in emerging CDS markets. Restructuring, on the other hand, is interesting for this work as it can be used (and it has been recently[25]) as a trigger event in developed countries, and because it represents one contractual difference with bonds.

[24] https://corporatefinanceinstitute.com
[25] One example in the sample is the Greek restructuring in 2012 that triggered credit default swaps Miller & Thomas (2013).

The so called “restructuring clause” is of relevance in this analysis as it modifies the price of the CDS. The table printed below shows the most frequently used restructuring clauses in CDS contracts.

Clause	Short name	Description
Old-Restructuring	Old-Re (OR)	This is the original standard for deliverables in default swaps in which the maximum maturity deliverable is 30 years.
Modified-Restructuring	Mod-Re (MR)	This is the current standard in the US market. It limits the maturity of deliverable obligations to the maximum of the remaining maturity of the swap contract and the minimum of 30 months and the longest remaining maturity of a restructured obligation. It only applies when the credit event has been triggered by the protection buyer.
Modified-Modified-Restructuring	Mod-Mod-Re (MMR)	This is the standard for the European market. It limits the maturity of deliverable obligations to the maximum of the remaining maturity of the CDS contract and 60 months for restructured obligations and 30 months for non-restructured obligations. It also allows the delivery of conditionally transferable obligations rather than only fully transferable obligations. This should widen the range of bonds/loans that can be delivered. It only applies when the credit event has been triggered by the protection buyer.
No-Restructuring	No-Re (NR)	This contract removes restructuring as a credit event.

Table 2: different types of restructuring clauses. Source: O’Kane, D., 2008. Modelling single-name and multi-name credit derivatives.

The “Old-Restructuring” (OR) clause (today is also called Cumulative Restructuring – CR) is the original clause in the standard contract set in 1999 by the ISDA definition. The Modified-Restructuring clause became popular in the U.S. in 2001 and is still the most common contract in the U.S. market. The Modified-Modified-Restructuring, as shown in table, is considered the standard in the European markets. Since 2003, it is the most common clause in CDS contracts with corporations as reference entities. Finally, the No-Restructuring (NR or XR) does not consider debt restructuring as a credit event that can trigger the protection leg.

It has been found[26] that the restructuring clause influence the CDS spread in a precise way: in particular, it is true that

$$S_{CR} > S_{MMR} > S_{MR} > S_{XR}.$$

Even if this relation is intuitively straightforward (because the wider the range of deliverable obligations in the contract, the higher should be the price that the buyer must pay), the exact spread difference is still an issue to determine, as it would require a precise estimation of the probability that any credit event is a restructuring and of the price dispersion of the deliverable obligations involved. However, this paragraph showed the importance of the restructuring clause, especially when comparing different CDS contracts, it is crucial that they have the same restructuring clause[27].

1.4 CDS pricing

Even before the introduction of CDS, there was extensive literature aimed at pricing credit risk. The first model, elaborated by Merton, is dated 1974. This model, that values corporate bonds using modern option theory, is still used today to understand how well a company is at meeting its financial obligations[28], and was then extended towards sovereign credit risk by Gapen et al. (2008). These models are known as structural models, as they price credit risk considering the whole structure of a firm.

Another branch in the literature exists, that specifically studied the pricing of CDS and elaborated a series of so called reduced-form models: while in structural models a default occurs whenever the total asset value of a firm falls below a certain boundary, these models follow an intuitive "no arbitrage" logic, considering default as a random stopping time with a stochastic arrival intensity (Zhu, 2006). Using this logic, the pricing of credit risk is determined by risk neutral valuation under the absence of arbitrage opportunities. Many authors, such as Das (1995), Duffie (1999), Acharya et al. (2002) and Hull and White (2000) used reduced-form models to price CDS.

[26] O'Kane (2003).
[27] The choice of the clause in my sample will be described in chapter 3, in the data description paragraph.
[28] Source: Investopedia.

1.4.1 Theoretical model

The method used in this thesis is similar to the one proposed by Duffie (1999) and by Hull[29], because it provides a convenient way to treat CDS in the same manner as bonds in the pricing procedure, and therefore it represents a good working framework for the objectives of this thesis. Pricing of CDS, in fact, is not a specific aim of this work, but it will be used in the PECS methodology[30] to convert bond spreads.

The idea behind this model is simple: since the value of a CDS at time 0 is zero (by definition), the spread is the amount that makes the cash flows of the protection buyer and of the seller equal.
To do so, the first step is to define the probabilities involved at time zero. They are:

- The cumulative default probability (QPDt) is the cumulative probability that the reference bond defaults between time 0 and time t. For example, if the QDP of a bond at year 2 is 0,02, there is 2% probability that the bond will default within the second year from today.
- The unconditional default probability (PDt) is the probability that the bond defaults between time t and time t-1: if a bond has a PD3 of 0,01, there is 1% chance that it will default between 2 and 3 years from now.
- The conditional default probability (λ_t), that I will call hazard rate or default intensity, is the probability that the bond defaults at time t, conditional on the fact that it did not default up to that point.
- The survival probability (Vt) is the probability that the bond survives at year t.
- The survival intensity (St) is the opposite of λ_t, or the probability that the bond survives in t, given the fact that it survived until time t.

These probabilities are linked by the following 5 relations:

1) $PD_t = QPD_t - QPD_{t-1}$
2) $PD_t = \lambda_t * V_{t-1}$

[29] Option, futures and other derivatives, ninth edition, Pearson.
[30] It will be described in chapter 2, paragraph 3.

3) $V_t = V_{t-1} - PD_t$
4) $V_t = 1 - QPD_t$
5) $S_t = 1 - \lambda_t$

Using these relations, is it possible to simulate the cash flows of the premium leg and the protection leg.

Assuming that there is a zero-coupon discount curve[31] (Zt), and that time is discrete, the present value of the premium leg is equal to:

$$PV_{premium} = \sum_{j=1}^{n} Z(t_j)V(t_j)\boldsymbol{s}dt + \sum_{j=1}^{n} Z\left(\frac{t_j + t_{j+1}}{2}\right) PD(t_j)\boldsymbol{s}dt/2\ ,$$

Where:

- the first factor is the sum of the normal periodic payments made by the buyer during the life of the contract[32];
- the second factor is the accrued coupon at default: since we cannot know a-priori the exact day in which the bond will default, the model assumes that every default happens exactly at mid-year[33].
- **s** is the spread of the CDS.

The protection leg is computed as follows:

$$PV_{protection} = (1 - RR) * \sum_{j=1}^{n} Z\left(\frac{t_j + t_{j+1}}{2}\right) PD(t_j)dt/2\ ,$$

where RR is the Recovery Rate.

Setting:

$$PV_{premium} = PV_{protection},$$

[31] A further explanation on the risk-free curve construction.

[32] Hence, during the life of the deliverable obligation.

[34] This factor captures the accrued coupon that we introduced in Figure 3 when introducing the settlement of a CDS contract.

and rearranging the term, one obtains the no-arbitrage (or fair) CDS spread:

$$\boldsymbol{s}^* = \frac{(1-RR) * \sum_{j=1}^{n} Z\left(\frac{t_j + t_{j+1}}{2}\right) PD(t_j) dt/2}{\sum_{j=1}^{n} Z(t_j) V(t_j) dt + \sum_{j=1}^{n} Z\left(\frac{t_j + t_{j+1}}{2}\right) PD(t_j) dt/2}$$

1.4.2 CDS pricing, a practical example

To be thorough, I present a practical example of the application of the formula proposed in the last paragraph.
The starting point for computing the fair CDS spread, is to extract a default term structure: in this example, for illustrative purposes[34], I used historical sovereign default probabilities sorted in different rating categories taken from the Standard and Poor's annual sovereign default and rating Transition Study (dated May 18, 2020)[35].

Table 3 shows the cumulative default rates observed by governments in the Rating Agency's database and covers more than 40 years of data.
From these cumulative probabilities, using the relations 1), 2) and 3), we compute the probability of default at time t (that we called PD_t), the probability of survival V_t and the hazard rate λ_t for any point in time. Here, we consider a bond issued by a "BB"-rated country with 5 years of maturity.

[34] In the PECS, the default term structure is assumed to be flat, i.e., the survival intensity is constant, as we will see in paragraph 2.3.
[35] https://www.standardandpoors.com/en_US/delegate/getPDF;jsessionid=555157E1E71DF03C299EAAB497E1991F?articleId=2487381&type=COMMENTS&subType=REGULATORY , p. 18.

Sovereign Foreign Currency Cumulative Average Default Rates Without Rating Modifiers (1975-2019)*

(%)	--Time horizon (years)--														
Rating	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
AAA	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
AA	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
A	0.00	0.00	0.26	0.81	1.38	1.97	2.59	3.24	3.92	4.65	5.45	6.31	7.24	7.77	8.94
BBB	0.00	0.47	1.22	1.76	2.32	2.94	3.60	3.97	4.36	4.79	5.25	5.75	6.28	7.43	8.05
BB	0.41	1.47	2.14	2.84	4.07	5.36	6.74	8.53	9.80	10.83	11.58	12.39	13.30	14.30	14.86
B	2.26	5.62	8.63	11.45	14.03	16.07	18.30	20.42	21.77	22.91	24.62	26.09	26.66	27.33	28.12
CCC/CC	38.64	45.72	53.86	56.57	59.47	65.26	68.15	68.15	68.15	68.15	68.15	68.15	68.15	68.15	68.15

Table 3: Sovereign cumulative default rates. Source: S&P Global Rating Research and S&P Global Market Intelligence's CreditPro®.

We then create a table (Table 4) with the three columns of values just calculated:

Time	*Hazard rate (default intensity)*	*Unconditional default probability (PDt)*	*Survival probability (Vt)*
1	*0,004*	*0,0041*	*0,9959*
2	*0,011*	*0,0106*	*0,9853*
3	*0,007*	*0,0067*	*0,9786*
4	*0,007*	*0,007*	*0,9716*
5	*0,013*	*0,0123*	*0,9593*

Table 4: Probabilities involved in the CDS price calculation. Source: author's elaboration.

The second step of the procedure is to simulate the cash flows of the seller and the buyer. Regarding the seller, a new table (Table 5) is filled out with the survival probability, the expected payments, and the discounted expected payments[36]. For the seller, the payments consist in the periodic spread paid by the buyer of protection, that are conditional on the fact that the bond survives each year, so they are computed as:

$$Exp\_payments_t = V_t * notional * s,$$

Where the notional is omitted since it will cancel out when computing s.

[36] Here, for simplicity, we assume a constant risk-free rate of 0.05.

Time	*Survival probability (Vt)*	*Expected payments*	*Present value of expected payments*
1	*0,9959*	*0,9959s*	*0,9473s*
2	*0,9853*	*0,9853s*	*0,8915s*
3	*0,9786*	*0,9786s*	*0,8423s*
4	*0,9716*	*0,9716s*	*0,7955s*
5	*0,9593*	*0,9593s*	*0,7471s*
Total			*4,2237s*

Table 5: Cash flows for the seller of a CDS. Source: author's elaboration.

The same considerations hold in the next table, that measures the accrual payments to the seller if a default occurs. As mentioned in the last paragraph, the credit event date is interpolated to be at half of each year, and this is considered in the discounting. The expected accruals are computed as:

$$Exp\_accrual_t = PD_t * notional * s.$$

The cash flows of the seller are printed in Table 6.

Time	*Unconditional default probability (PDt)*	*Expected accrual*	*Present value of expected accrual*
0,5	*0,0041*	*0,00205s*	*0,0020s*
1,5	*0,0106*	*0,0053s*	*0,0049s*
2,5	*0,0067*	*0,00335s*	*0,0030s*
3,5	*0,007*	*0,0035s*	*0,0029s*
4,5	*0,0123*	*0,00615s*	*0,0049s*
Total			*0,0177s*

Table 6: Expected accrued coupon for the seller of a CDS in case of default. Source: author's elaboration.

The next step is to simulate the cash inflows of the buyer in case of a credit event, or the expected payoff or the contract

$$Exp\_payoff_t = PD_t * notional * (1 - RR),$$

Where RR is the Recovery Rate of the bond (assumed at 40%), and the same considerations mentioned before on the notional and the time interpolation hold.
The buyer's cash inflows are displayed in Table 7.

Time	*Unconditional default probability (PDt)*	*Recovery Rate*	*Expected payoff*	*Present value of expected payoff*
0,5	*0,004*	*0,4*	*0,0025*	*0,0024*
1,5	*0,011*	*0,4*	*0,0064*	*0,0059*
2,5	*0,007*	*0,4*	*0,0040*	*0,0035*
3,5	*0,007*	*0,4*	*0,0042*	*0,0035*
4,5	*0,012*	*0,4*	*0,0074*	*0,0059*
Total				*0,0213*

Table 7: Expected payoff for the buyer of a CDS contract. Source: author's elaboration.

Once all the cash flows are computed, the fair spread is set to make the swap transaction an equal trade for the parties at time zero.
According to the CDS pricing equation proposed in paragraph 1.4.1, we have that:

$$\sum PV\ of\ exp.Payments * \boldsymbol{s} + \sum PV\ of\ exp.Accrual * \boldsymbol{s} = \sum PV\ of\ exp.\ Payoff$$

Rearranging:

$$\boldsymbol{s} = \frac{\sum PV\ of\ exp.\ Payoff}{\sum PV\ of\ exp.\ Payments + \sum PV\ of\ exp\ \ Accrual} = 0{,}00501387$$

Thus, the fair CDS spread is 50,1387 basis points.

Chapter 2

The CDS-bond basis

While the first chapter introduced the main features of credit derivatives and CDS, the aim of this chapter is to describe how the world of credit derivatives is linked to debt markets. The first paragraph describes the theoretical no-arbitrage relation that links these two worlds and some theoretical reasons behind the deviations from equilibrium, the second paragraph contains an extensive literature review on the matter, and the third one contains the PECS method, used in the empirical analysis compare bond spreads and CDS spreads.

2.1 A fully hedged portfolio with a bond and a CDS

As seen so far, credit default swaps are aimed at covering the possible losses on the principal of the reference obligations in case of default. In this paragraph, I show that an investor can, under some assumptions, build a perfectly hedged portfolio[37] just by taking positions on a bond and a CDS on the same bond.

The first assumption needed for this theoretical relation to hold is that the bond is a floating rate note trading at par (for example, with a face value and a trading price of $100) with a maturity T equal to the maturity of the CDS. The second assumption is that the investor funds the purchase of $100 of face value of the bond through a repo[38] transaction, at a certain rate (repo rate = risk-free rate + R[39]).

To hedge the default risk of the Floating Rate Note, the investor simultaneously enters in a CDS contract with notional $100 of the same FRN and the same maturity, T. In doing so, the investor has transformed his risky position into a risk-free one.

Figure 5 shows the situation described above.

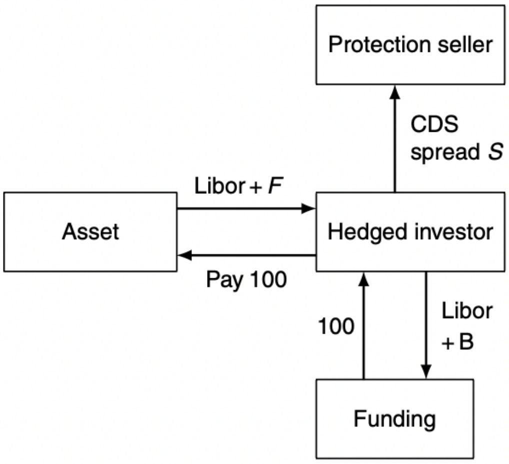

Figure 4: The hedged portfolio. Source: O'Kane, D., 2008. Modelling single-name and multi-name credit derivatives.

Assuming that the FRN pays a spread of F above the risk-free rate, and that the CDS spread is s, the payoff of the portfolio for the investor, when there is no credit event, is:

$$P = 100 - RFR - R - 100 + RFR + F - s = F - R - s$$

[37] Meaning that the portfolio will generate a return equal to the risk-free rate under any circumstance.

[38] Repurchase agreements (or repo transactions) are short term loans backed by a collateral.

[39] R is the spread of the repo transaction over the risk-free rate that the investor has to pay to fund the purchase of the bond.

In the scenario of a no credit event, at maturity T the CDS contract terminates, and the investor receives \$100 of face value of the bond and uses it to repay the funding. So, the net cash flow of this portfolio at maturity is zero.

In the scenario of a credit event occurring before the maturity of the portfolio, the hedged investor can deliver the defaulted FRN to the protection seller[40], receive \$100 of face value and use the \$100 to repay the funding. Even in this case, for the investor, the net value of the cash flows at the termination of the portfolio is \$0.

Since the portfolio is perfectly hedged and it has no initial cost, the investor should not earn or lose anything from it at any payment date. This means that

$$P = F - R - s = 0 \, .$$

Rearranging:

$$s = F - R \, .$$

So, the CDS spread is equal to the Par Floater spread minus the cost of funding.

2.1.1 The CDS-bond basis

In the last paragraph, I showed how an investor can build a fully hedged portfolio using a bond and a CDS on the same bond. A portfolio like this establishes a first relation between bonds and CDS and allows us to write the spread of a CDS as a function of the rate of a floating rate bond and the funding spread. However, in the sovereign bond markets, floating rate bonds have usually smaller trading volumes, being the fixed coupon bonds way more common.

Assume, this time, that an investor is already holding a sovereign fixed-coupon bond yielding Y. If he wants to hedge against the credit risk of the issuer government without

[40] Here, we assume the CDS is physically settled. In case of a cash settled CDS, the investor receives \$100-RR from the protection seller, then sells the defaulted bond in the market for RR and uses the \$100 to repay the funding.

selling the bond, he could take a long position on a CDS on that bond, with the same maturity of the bond. Similarly to what we saw before, the investor has eliminated the default risk associated with the bond, which is now a riskless asset. Therefore, this portfolio should theoretically earn exactly the Risk-free rate[41]:

$$Y - s = RFR \ ,$$

where Y is the yield-to-maturity of the bond, s is the CDS spread and RFR is the Risk-free rate.
By moving all the terms to the left and changing the sign, we obtain:

$$s - (Y - RFR) \ = 0 \ \ .$$

The left-hand side of the equation is called CDS-bond basis, and the relation shows that, absent any frictions and arbitrage opportunities, it should always be zero.

2.1.2 Speculative strategies with the basis

So far, we have demonstrated that the CDS-bond basis should be zero based on some reasonable assumptions. The demonstration is based on the no-arbitrage argument, stating that the basis cannot differ from zero for a significant amount of time, because arbitrage forces will drive it quickly to zero. In this paragraph we will see some possible ways to exploit positive and negative deviations of the basis, and how a theoretical speculator could make free money from a strategy with bonds and CDS when the basis is non-zero.
In the first scenario, we assume that

$$Spread_{CDS} - \ Spread_{bond} > 0$$

Where $Spread_{bond}$ is the yield of the bond above the risk-free rate.

[41] Further considerations on the Risk-free rate will be done in paragraph 2.3.

In this positive basis scenario, if a speculator wants to make profit from the basis trade, he should short-sell the bond via a reverse-repo transaction and simultaneously sell protection on the bond. This portfolio is similar to the one seen in paragraph 2.1, but with opposite operations: as before, the cash flows for the speculator, at the termination of the portfolio, sum to zero. But having sold protection on the bond, he collects the periodical spread of the CDS, which is greater than the bond spread he must pay. With this strategy, an arbitrageur can lock-in a risk-free annuity equal to the basis.
In the second scenario, assume that

$$Spread_{CDS} - Spread_{bond} < 0$$

In this case, the basis is negative, and an arbitrageur can go long on the bond (either by own funding or by a repo) and buy protection on the same bond. This portfolio, as seen in paragraph 2.1, is risk-free and the same considerations mentioned in the positive basis scenario hold.

2.1.3 Theoretical determinants of the basis

Before discussing all the relevant empirical findings on the CDS-bond basis, it is necessary to point out some factors that, intuitively, can drive it away from zero. So far, we have made some assumptions to establish the link between CDS and bonds. We assumed that the bond is a par floating rate note, that the bond and the CDS have the same maturity, and that the notional of the CDS is the same of the face value of the bond. We also described some simple ways in which it is possible to make an arbitrage with basis trades. Although these assumptions seem reasonable, many contractual and market factors may generate a misalignment in the prices of bonds and CDS. Moreover, some frictions that prevent arbitrageurs to fully exploit the misalignment exist and make basis trades non-applicable or non-convenient.

2.1.3.1 Contractual (or fundamental) factors

Even if CDS and bonds have similar characteristics in terms of credit risk exposure, some contractual (or fundamental) aspects can make their prices diverge. The most relevant to this work[42] are listed below.

- FUNDING ISSUES: while bonds are financial assets and have a face value and a trading price, CDS are derivatives contracts where the notional is used to compute the spread, but never exchanged by the parties. Furthermore, the purchase of a bond is funded (for example, at LIBOR[43]), while the purchase of most CDS is unfunded. However, since not all market participants can fund the purchase of bonds at the same rate, the purchase of bonds is favored by investors that fund below the LIBOR rate, while CDS are favored by those who fund above. This factor drives the basis away from zero based on how the market is composed. Generally, most of the cash investors fund themselves above the LIBOR, so this factor tends to move the basis in the negative field.
- The “CHEAPEST-TO-DELIVERY” option: in paragraph 1.3.3, we mentioned the restructuring clause as a possible contractual driver of the basis. Whenever restructuring is considered a trigger event for the protection leg of the CDS, the contract allows the protection buyer to choose among a range of deliverable obligations. In other words, the CDS gives the buyer an option on the deliverable obligation, that, in some cases, may be valuable. If a deliverable asset which is cheaper than the reference entity exists in the market, the buyer can just sell his defaulted asset in the market, buy the cheaper one and deliver it, making a profit. Since bonds don’t offer this kind of option to the buyer, this factor makes - ceteris paribus – CDS to be more valuable, driving CDS spreads above bond spreads, and therefore the basis to be positive.
- TECHNICAL DEFAULT: since the set of trigger events for a CDS is usually broader than the default of bonds, CDS spreads should be higher, being the triggering of the protection leg more probable than the default of a bond. This factor moves the basis upwards.

[42] This part is based on de Wit (2006).
[43] London Inter-Bank Offered Rate.

- BONDS TRADING AWAY FROM PAR: CDS contracts usually guarantee the reference entity for a par amount. However, especially after an issuance, the bond price can deviate substantially from par, for example, after a change in interest rates. When there is an increase in interest rates and bond prices fall below par, the CDS spread increases because protection sellers guarantee for an amount which is greater than the value of the reference entity. Hence, the basis increases. By contrast, when rates decrease, the basis decreases. This factor is peculiar as it is the only one determined by a "mathematical" effect and is easy to measure.
- CDS SPREADS ARE FLOORED AT ZERO: as we will see in the empirical analysis, CDS spreads cannot be negative, because the cost of the contract should at least cover the administration cost of the CDS trade (O'Kane, 2008). Moreover, no protection seller would accept to offer protection, even for the most remote event, for a negative spread. Bonds, instead, could easily show negative spreads if the issuer (usually a government official) is deemed to be more creditworthy than the commercial banking sector[44]. This issue will be better explained in Chapter 3, regarding the choice of the risk-free rate.
- ACCRUED COUPON AT DEFAULT: as seen in paragraph 1.3.1, when a default occurs, the buyer must pay to the seller the premium accrued between the last payment date and the default. We also mentioned this accrued coupon discussing about CDS valuation using a reduced form approach: watching the equation (((PARAGRAPH 1.4.1 for s*) it is intuitive that the effect of the inclusion of the accrued coupon is an increase in the denominator and, ultimately, a reduction of the spread. When a bond defaults, instead, the claim of the creditor is on the entire face value, but not on the accrued coupon. Hence, the overall impact of this factor on the basis is negative.

2.1.3.2 Market factors

As the name suggests, these basis drivers are a consequence of the market structure in which bonds and CDS are traded. They consist in a series of frictions and phenomena characterizing markets, that prevent the two prices to converge. While contractual drivers

[44] See paragraph 3.1.1 for a more detailed explanation.

can be avoided (or contained) with a correct choice of contracts to include in the sample, market factors have been the topic of several studies in literature[45], as they can usually be empirically observed. As in the previous paragraph, below is a list of the most relevant market factors.

- SHORT SELLING FRICTIONS: In the last paragraph we have seen how arbitrageurs can exploit a positive basis by selling protection in the CDS market and selling the reference entity. However, short-selling a bond is not always easy and feasible in the market: the bond may not be available, or the reverse-repo rates may be too low for the arbitrageur and represent an opportunity cost (Fontana and Scheicher, 2015). Moreover, when there is an increase in the demand protection on an issuer, most participants prefer buying protection in the CDS market rather than short selling in the cash bond market. The effect of these frictions is, obviously, an increase of the basis.
- SYNTHETIC CDO[46] TECHNICAL SHORT: this is purely a technical aspect that impacts the basis. Whenever an originator wants to sell synthetic credit risk to investors, it needs to cover its position by hedging in the CDS market, going long on credit risk, and thus selling CDS. This factor, even if hard to estimate correctly, is considered an important reason for the depression of the basis.
- RELATIVE LIQUIDITY: this factor is a direct consequence of the demand and supply dynamics. The Bond and CDS market are populated by different participants and with different purposes. While the main players for bonds (insurance companies, pension funds and central banks) have buy-and-hold funded strategies, in the CDS markets there are banks, hedge fund and proprietary trading desks. This creates a misalignment in the liquidity points between cash bond and CDS markets. This happens mainly because issuers of bonds drive the liquidity of the market according to their financing needs, while in the CDS markets the liquidity is high at fixed maturities of three-years, five-years, ten-years and close to zero in other points in the curve. This liquidity mismatch can result in a difference in the basis as a function of maturity. In general, the basis will decrease where CDS are more liquid and increase when bond liquidity is higher.

[45] Most of them will be listed in the literature review (paragraph 2.2).
[46] Collateralized Debt Obligations: they are structured credit derivatives backed by a basket of assets that serve as collateral if the loan defaults (source: Investopedia).

- FUNDING RISK: this factor is similar to the first contractual factor considered in the previous paragraph and derives from the unfunded nature of CDS. Since these contracts are unfunded, they allow the investor to reduce the cost opportunity (or the funding risk) by investing at LIBOR during the life of the contract. This should decrease the net CDS spread and thus have a negative impact on the basis[47].
- QUOTATION CURRENCY[48]: a typical market factor that makes the CDS and bond prices diverge is the different denomination currency. Eurozone sovereign bonds, for example, are denominated in Euro while their correspondent CDS are quoted in USD. The different denomination currency may affect the basis: suppose an investor wants to hedge his Eurozone bond position by buying protection in the CDS market. If a default occurs in the EU, the Euro is likely to weaken against the dollar: since the protection is dollar-denominated, this will result in a windfall profit for the investor. Besides the protection against credit risk, CDS contracts denominated in USD on Euro-denominated bonds provide the investor insurance against the depreciation risk. If depreciation after a default is seen as likely by the market, CDS spread in dollars should trade at a premium, hence increasing the basis.

Table 8 summarizes the theoretical factors described above and shows the sign of their effect on the basis.

[47] Bonds are funded, so this factor only impacts CDS spreads.
[48] O'Kane (2012), Fontana and Scheicher (2015).

Fundamental factors	*Funding issues*	*(+) (-)*
	"CHEAPEST-TO-DELIVERY" option	*(+)*
	Technical default	*(+)*
	Bonds trading away from par	*(+) (-)*
	CDS spreads are floored at zero	*(+)*
	Accrued coupon at default	*(-)*
Market factors	*Short selling frictions*	*(+)*
	Synthetic CDO technical short	*(-)*
	Relative liquidity	*(+) (-)*
	Funding risk	*(+)*
	Quotation currency	*(+)*

Table 8: Theoretical determinants of the basis. The third column contains the expected impact on the basis. When both signs are present, the impact is uncertain or not unilateral. Source: author's table based on De Wit (2006).

2.2 Literature review

Spread determinants of bonds and CDS have been extensively studied since the mid-90s. The theoretical framework on credit spread determinants founded by Merton (1974)[49], was further expanded by many authors. Elton et. al (2001), for example, explained bond spreads by means of expected loss on default, tax premium and risk premium. They based their study on a sample of corporate bonds and found that bond spreads have some similar features to stock spreads. Another study by Collin-Dufresne et-al (2001)[50] found that, for a set of industrial bonds, the explanatory power of credit-risk factors and proxies for liquidity is rather limited and suggested that spreads move accordingly to local supply/demand shocks. An important study by Chen et. al (2007)[51] based on a sample of 4000 corporate bonds, updated the credit spreads literature, finding an inverse relation between bond yields and liquidity measures. This confirmed the fact that bond yields cannot be fully explained only by means of default risk determinants.

[49] See paragraph 1.4.
[50] The determinants of credit spreads.
[51] Corporate yield spreads and bond liquidity.

There is also an extensive paper specifically addressing the determinants of CDS spreads. Besides the literature already cited in paragraph 1.4.3 regarding the valuation of CDS, there are several other worth-noting studies useful for this work. Longstaff et al. (2005), with an apparently contrasted result with Chen et al. (2007), studied the information given by CDS spreads to argue that most bond yields are explained by default risk factors, while the nondefault factor is linked to liquidity factors. Some of these default factors, as pointed out by Ericsson et al. (2009) are volatility and leverage, which are both found to be statistically significant in explaining credit spreads. A more recent study, conducted by Galil et al. (2014)[52], tried to explain the movements in CDS spreads involving a broad dataset of 718 U.S. firms and for a long period of time (from early 2002 to early 2013): their results were more in line with structural models for credit risk pricing; moreover, they added that previous models in literature could have been improved by adding some market conditions in the set of explanatory variables.

Although these findings are crucial in assessing how CDS spreads and bond spreads – *per sé* - are influenced (the study of their dynamic relation and the misalignment in their prices is the very aim of this work), a more useful branch in literature is the one specifically regarding the basis.

To better organize the review, the next two sub-paragraphs distinguish between the literature covering the basis in the corporate sector and the sovereign sector.

2.2.1 Corporate sector

In the corporate sector, Blanco et al. (2005) analyzed the dynamic relation between bonds and CDS for a set of U.S. and European companies during the non-crisis period of 2002/2003: even if the purpose was to study the price discovery process, they observed that the parity relation held reasonably well in that period and supported the theory of a long-term equilibrium between the two prices. Moreover, some short-run deviations (with a positive basis) were observed and explained by the repo cost of short selling bonds and by a lead for CDS in the price discovery.

52 https://www.sciencedirect.com/science/article/pii/S0378426613004676?casa_token=wEIvWjjv3TMAAAAA:rQE_KmAU1yNyPGnMeLvzu7DqCnyMswW_A2lYX2ca78ilGh4UUVbRKAGWeqhbXe_GSBf4a-fz8NE#b0045

The long run relation tying the two prices together was also confirmed by Zhu (2006), who considered a larger period for his observation (1999-2002). The Wit (2006) extended previous literature, confirming the existence of a positive basis in the corporate sector during the period 2004-2005. Some later studies in the corporate sector tried to explain the positive basis: Nashikkar et al. (2007) documented a persistent positive (but decreasing) basis in the period spanning from 2002 to 2006 in a sample of more than 5700 bonds and suggested that liquidity in the CDS market played a role in the deviation from parity. This article is useful because it adopted the Par Equivalent CDS Spread used in this thesis to compare CDS and bonds: we willl explain this method in the next paragraph. In the same manner, Trapp (2009) explored the profitability of trading the basis and showed that basis size is related to company-specific credit risk, liquidity, and market conditions. Two important contributors to this field are Bai and Collin-Dufresne, that published a series of articles studying the CDS-bond basis in the corporate sector in more recent times, especially during and after the financial crisis in 2008. Their 2019[53] article is convenient as it summarises how the basis evolved before, during and after the crisis. In particular, they showed that the basis inverted its dynamic, remaining in the negative field for almost the entirety of the sample, both for investment grade and high yield bonds. They divided the period of observation (from 2006 to 2015) into four sub-periods and observed episodes of extreme negative basis in the period going from July 2007 to September 2009 (which was during the crisis). They used a cross-sectional approach to demonstrate that several limits-to-arbitrage measures (such as bond illiquidity, counterparty risk, funding risk and collateral quality) have had a strong influence on the behaviour of the basis. Overall, this article is consistent with what we discussed in paragraph 2.1.3 about frictions that prevent traders to exploit the basis.

2.2.2 Sovereign sector

I chose to keep the literature of the sovereign sector separate from the one of the corporate sector for two main reasons: firstly, to highlight the empirical similarities and differences in literature, and secondly because studies regarding this matter in sovereign markets have

[53] Bai and Collin-Dufresne (2019).

had a different path than corporate ones. In fact, the first study regarding sovereign credit spreads was rather scarce and did not directly address the CDS bond basis[54].

The first papers investigating the behavior of the basis are quite recent and limited to emerging markets: Ammer and Cai (2011) identified the "cheapest-to-delivery" option as the main driver of the positive basis in emerging markets between 2001 and 2005. Another study conducted by Küçük (2010) studied the basis for 21 emerging market countries between 2004 and 2008 and found that it can be related to liquidity, equity market performance and macroeconomic factors.

Although these studies are useful to identify some possible drivers to include in this analysis, I dedicated the last part of this review to literature covering Eurozone developed countries, which I aim to extend.

Historically, the sovereign credit market of the EMU[55] can be divided into 2 periods. The first, going from the adoption of a single currency in 1999, characterized by a significant convergence in bond yields for a vast majority of the countries, seen as a direct effect of the introduction of the Euro and of the role played by the ECB in maintaining price stability. In this period, literature covering the CDS bond basis is almost absent since bond spreads (and credit spreads in general) over the German Bund were close to zero. The beginning of the second period can be attributed to the collapse of Lehman Brothers in September 2008 and conventionally starts in Europe in mid 2010, with the beginning of a period of huge market turmoil and credit stress, known as the sovereign debt crisis. In this period, the yields of several Eurozone bonds experienced an unprecedent divergence, with the most vulnerable countries (Ireland, Portugal, Spain, and Italy) being also the most damaged ones.

These events attracted the attention in the literature similarly to the corporate markets in this period, as several positive and negative basis episodes emerged. Several authors began to investigate possible drivers of the basis[56]: There are two main studies that inspired this work, for the methodology they used, and the countries considered: Arce et al. (2013) and Fontana and Scheicher (2015). Arce et al. (2013), obtained significant explanatory power of factors as counterparty risk, funding risk and relative liquidity between the two markets basing on a sample of 5-year bond yields and CDS spreads for

[54] See Codogno et al. (2003), Geyer et al. (2004) among all.

[55] European Monetary Union.

eleven EMU countries. They also explored the impact of the ECB, that implemented a programme of sovereign bond purchases in the secondary market (the SMP[56]) in order to address bond liquidity problems and guarantee a correct monetary transmission: it was found to be significant and positive on the basis.

Regarding the impact of the ECB during the crisis, similar results were found by Fontana and Scheicher (2015), who argued that the effect of the ECB is twofold: first, being the ECB a big “buy and hold” investor[57] in the secondary market, it increased the liquidity of bonds; on the other hand, since most of the bond purchased by the ECB were not repoed out, this caused a lack of bonds to short-sell, representing a considerable “short-selling friction” for positive basis traders.

What makes these articles interesting is the fact that they found two different paths for the basis in their samples: while, in the more robust and financially sound EMU countries (the “core” countries) persistent positive bases were observed, in countries that already had weak public finances and high levels of debt (called “peripheral” countries) bases were negative. Fontana and Scheicher (2015) attribute to short selling frictions the positive bases in “core” countries, and to funding liquidity the negative bases. Furthermore, they included a “flight-to-quality” factor, that is, the phenomenon in which in a distressed period, investors tend to rebalance their holdings shifting towards less risky and more liquid assets[58]: they found it to be present and significant in explaining this twofold behavior of the basis.

This thesis shares some of the objectives pursued by these articles, with two main differences: firstly, I aim to study the behavior of the basis before and during the Coronavirus outbreak in developed countries, so my model contains specific dummy variables connected with the pandemic. Secondly, I add a methodology, the PECS, for the computation of the basis. To my best knowledge, this is the first study to implement this methodology for developed European countries: so far, its application has been limited to the corporate and emerging market sovereign sectors, that have, in general, a higher perceived credit risk.

[56] Securities Market Programme.

[57] Corradini and Maddaloni (2015).

[58] https://www.investopedia.com/terms/f/flighttoquality.asp#:~:text=Flight%20to%20quality%20refers%20to,quality%22%20during%20rough%20economic%20patches.

2.3 Converting bond spreads into CDS spreads: the PECS methodology

The Par Equivalent CDS Spread is a procedure developed by JP Morgan[59] and adopted by many practitioners to calculate the CDS-bond basis. Even if it involves a series of calculations that are not straightforward, it represents a convenient and meaningful way to compare CDS and bonds, as it provides an apple-to-apple measure across the CDS and cash bond spreads[60].

In fact, similarly to the CDS valuation method presented in paragraph 1.4.2, the valuation of the bond under the PECS methodology is based on default and survival probabilities[61]. While a risk-free bond's price can be computed as the sum of the present values of its cash flows (coupons plus principal), in a risky bond there is the possibility that the issuer defaults. So, the cash flows must be weighted for the probability that it survives until the payment becomes due. For this reason, when pricing a bond in a risky context, two scenarios should be considered:

1 The bond survives until maturity: all the cash flows are paid, including the notional principal (face value).

2 The bond defaults before the maturity: the coupon payment stops, and only a fraction of the principal can be claimed. This quantity depends on the recovery rate of the bond, which is assumed to be the same of the reference bond of the CDS contract.

In this framework, the price of a risky bond, at time zero, is:

$$P_0 = C * \sum_{i=1}^{N} DF(t_i)V(t_i)dt + 1 * DF(t_N)V(t_N) + RR * \sum_{i=1}^{N} DF(t_i)PD(t_i)dt \, ,$$

where:

i. C is the bond's coupon (expressed in absolute terms, not as a percentage).

ii. $DF(t_i)$ is a discount factor (for now, we assume it to be the risk-free rate).

[59] This section is based on Elizalde et al. (2009).
[60] Bai and Collin-Dufresne (2019).
[61] In this paragraph, we adopt the same notation used in paragraph 1.4.2.

iii. RR is the recovery rate.
iv. The first factor is the present value of the expected coupon payments.
v. The second factor is the present value of the expected principal payment at maturity.
vi. The third factor is the present value of the fraction of the principal recovered in case of default.

Although the equation assumes an annual coupon frequency, the formula is similar (with some adjustments for the discount factor) for other frequencies. In any case, the formula assumes that the credit event can only occur at the date of the coupon payment[62].
Notice that, to compute P_0, we still need the survival probability and the default probability for each year: the PECS extracts these probabilities directly from the full CDS curve traded in the market for the same bond. In fact, starting from the spread, we can reverse the calculations from paragraph 1.4.2 and get to the CDS-implied term structure of hazard rates that we can use to price the bond.

Now that we have all the elements, we can compute P_0, which is the price of the bond coherent with the CDS-implied default term structure. This price will almost surely be different from the market price of the bond (P_{mkt},). For this reason, we must apply a parallel shift to the default term structure to match the market price.
This shift must be positive if $P_0 > P_{mkt}$, and negative otherwise[63].
Once we match the bond's market price, we use the default term structure we obtained and convert it back to a CDS spread, which is called the Par Equivalent CDS Spread. This spread shares the default term structure's shape with the CDS (as we applied a parallel shift), and assumption on the recovery rate of the bond.

Finally, we can define the basis as:

$$Basis = CDS_t - PECS_t$$

[62] This assumption is similar to the one made for the accrued spread of a CDS at default.
[63] This is because the higher is the default risk, the lower is the bond's price.

This methodology has the advantage of solving any bias regarding the bond trading away from par.

However, it has some disadvantages: firstly, the computations are not straightforward (especially for daily observations). Secondly, finding bonds with the correct maturities to match with CDS.

To solve this second issue, in this thesis I selected a set of bonds maturing between 4.5 and 5.5 years (through the whole sample period) for each country and built a continuous bond price time series by combining consecutive bonds.

Even though this is a further approximation, the PECS should still be more precise in the computation of the basis than any other methodology.

Chapter 3:

Empirical analysis

The objective of this work is to check whether the zero-basis relation between CDS and bonds held before and during the Covid-19 pandemic or if was violated. Moreover, the work aims to extend the empirical research of this matter on European developed countries, that have been the least studied in the last decade.

In many of the past crises several basis episodes emerged. Therefore, I expect to find deviations in the basis, especially after the pandemic outbreak. A crucial point in this analysis is to try to explain what happened to the CDS and bond markets and how the pandemic impacted on these markets. To do so, a series of multiple linear regressions (containing plausible explanatory variables) are run on the basis during the observation period, aiming to identify its drivers. Another interesting matter addressed in this thesis is the analysis of the impact of the ECB's interventions to face the emergency.

The first paragraph contains the descriptive statistics of the sample, graphical representations of the data and some hypotheses and considerations.

The second paragraph contains the factors considered in the analysis and the sources of information.

The third paragraph contains the results of the regressions and comments on the estimated coefficients.

3.1 The data

Since this study aimed to maintain a line of continuity with previous research, in order to make the results comparable, the dataset contains a sample of nine selected Eurozone countries (Austria, Belgium, France, Germany, Greece, Italy, Netherlands, Portugal and Spain). By contrast, the data covers a period starting from the beginning of March 2018 to the end of April 2021. The 5-year benchmark yields for the nine countries are downloaded from Bloomberg, while the data source for the 5-year CDS spreads is extracted from the Credit Market Analysis database, which is a reliable source of quoted CDS spreads since 2004. The motive why I chose the 5-year maturity is because 5-year CDS contracts are by far the most traded for the sovereign sector, making them more comparable to the corresponding bonds[64].

3.1.1 Choice of the spreads

To decide the appropriate benchmark from the bond yield (which is the risk-free rate) I considered a series of factors. The choice of the spread, in fact, is crucial in the basis computation. In general, there are two commonly used spreads: the first one is the asset swap spread, which is a sort of spread over LIBOR (in my case, above the Euribor), and the second one is the bond yield spread above a benchmark bond (for Europe, the yield of the German bund). The LIBOR is generally considered a good proxy for the risk-free rate. However, since it is a reference rate for inter-bank lending, it embeds a compensation for the default risk of the banking sector[65]. Sometimes, when a country is deemed to be

[64] The relative liquidity between CDS and bonds has already been identified as a theoretical driver for the basis in paragraph 2.1.3.2.

[65] O'Kane (2012).

more creditworthy than the whole banking sector, its bond yield can trade way below LIBOR, affecting the basis positively, since CDS spreads are floored at zero[66].
Since we live in a period of extremely negative sovereign yields, the German bond traded at lower levels than the LIBOR for the whole sample period. So, to avoid a systematic bias in the basis, I chose the German bund yield as the benchmark yield for the simple basis computation.
For the PECS computations, instead, as a discount factor, I used the so called Zero Swap Curve, obtained from the Euribor and the euro swap rates for each maturity. Since the only maturities available on Bloomberg for this curve were annual, I used a bootstrap methodology[67] to extract the equivalent zero-coupon curve with the missing maturities I needed. Moreover, I used a cubic spline interpolation to obtain a weekly discount curve from monthly observations.

3.1.2 Descriptive statistics

Similarly to what has been done in previous research, I split the countries in my sample between "core" and "peripheral" countries, the former being the historically sound and well-financed ones (Austria, Belgium, France, Germany, and Netherlands) and the latter being the less sound ones (Greece, Italy, Portugal and Spain[68]). This methodology allows one to study whether a symmetric shock like the pandemic could have caused asymmetric effects on different groups of countries and to study the cross-sectional impact of the explanatory variables on the average movements of the basis.

Figure 5 shows the time series of the bases. The first aspect to note in this figure is that, around the beginning of March 2020 there seems to be a structural break, with an increase of almost every time series for all the countries of the sample. The date of this event coincides with the WHO's pandemic declaration (which was on the 11th of March 2020[69]), that has presumably contributed to the increasing of the perceived default risk, causing instability across the markets and a misalignment in prices.

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[66] See paragraph 2.1.3.1.
[67] The methodology is taken from Hull, J.C., 2015. Options, futures and other derivatives (ninth edition).
[68] These countries are sadly known as the PIIGS, for their historical tendency to have weak public finances and high level of debt/GDP. Ireland was excluded from the sample because of paucity of data for the CDS market.
[69] This date is marked by vertical lines in the plots. The horizontal lines mark the zero basis.

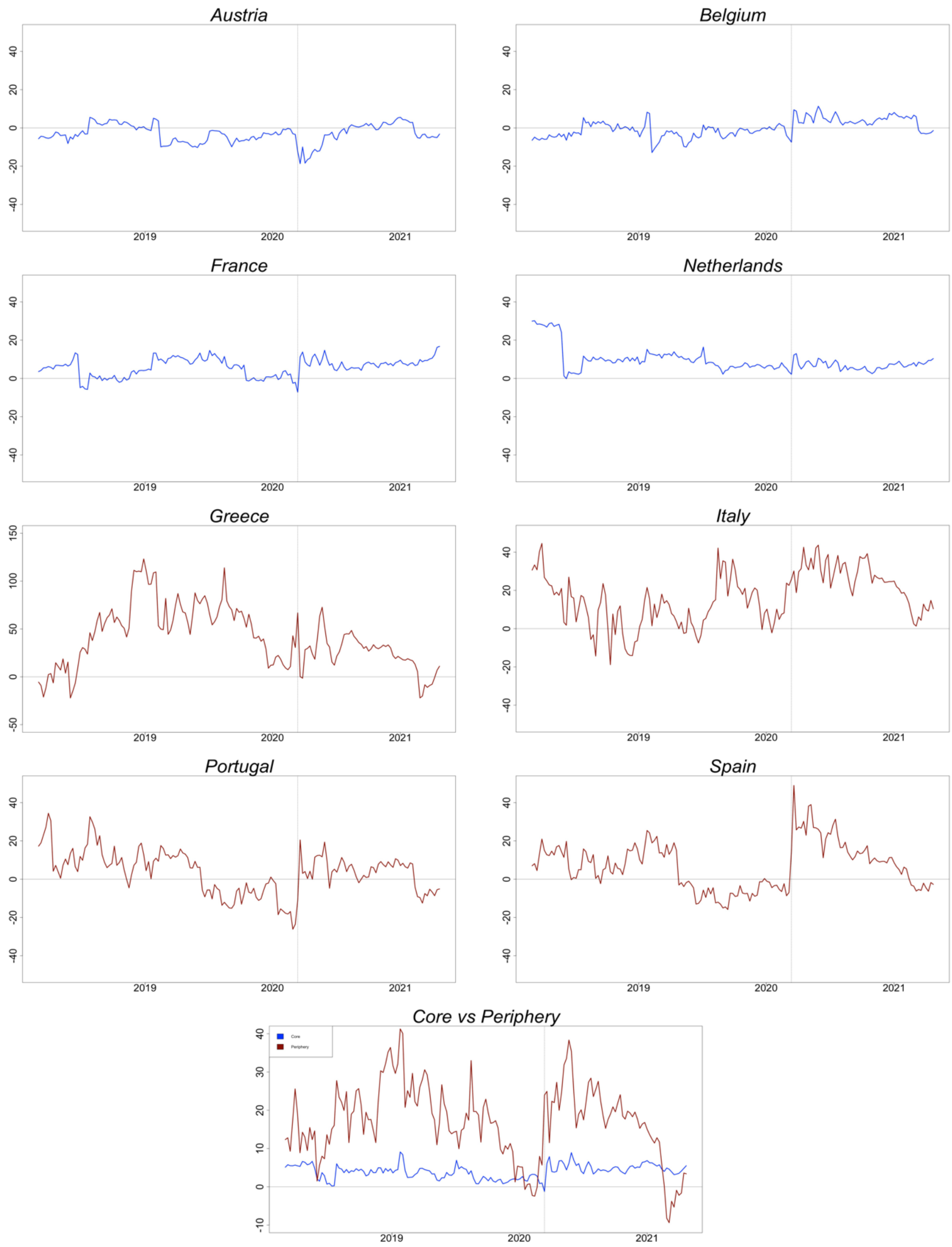

Figure 5: the CDS-bond basis for 8 EMU countries in the sample. The last plot contains the average basis in the core (blue line) and peripheral (red line) countries. Germany is excluded as the German bond yield is taken as the benchmark. Greece's y-axis is rescaled. Source: author's elaboration of Bloomberg and CMA databases.

Positive breaks are clearly visible in Spain and Portugal, with a sharp increase of 40 bps in both time series. Greece and Austria show negative breaks around the declaration.

Overall, by looking at the "Core vs Periphery" plot of Figure 5, it's evident that, while the core countries aggregate basis never exceeded 10 basis points, several positive spikes (up to 40 bps) emerged in peripheral countries.

Since the pandemic declaration seems to have influenced the behavior of the time series, I decided to split the calculation of the descriptive statistics into two subperiods, to measure how the basis changed before and after the declaration. The first subperiod goes from 02/03/2018 to 06/03/2020, and the second ends on April the 23rd, 2021. The break date chosen is the closest point from the pandemic declaration[70] I found in the database.

Table 9 shows the descriptive statistics for the bond yields, the bond spreads above the German bund, the CDS spreads, and the basis.
What's noticeable by looking at Table 9 is that the basis in core countries remained at low and positive levels through the whole period (with an average value of 4 basis points). The pandemic increased the basis by 1,5 basis points on average, shifting it from 3,5 bps to 5,0 bps. Austria was the only country that showed a negative average basis in the whole period. Regarding the peripheral countries, while the average basis remained virtually unvaried (around 17 bps in both the subperiods), when looking at individual countries some interesting paths in the basis appear. In particular, for Italy and Spain, the basis increased on average by 10 bps during the crisis. Greece on the other hand, showed an opposite behavior as the average basis decreased sharply from 49,8 bps to 24,3 bps during the crisis. These countries are the most interesting case studies as they (apparently) offered important arbitrage opportunities.

From a first look at the data, the overall positive behavior seems more attributable to the steady decline of bond yields rather than to the CDS spreads. In fact, with respect to the pre-crisis period, bond spreads decreased from 9,5 to 8,5 basis points in the core countries and plunged from 136,4 to 83,7 bps in the peripheral ones, while the average CDS spreads

[70] That is March 13th, 2020.

Country	*Period*	*Bond yield*		*Bond spread*		*CDS spread*		*Basis*	
		Mean	*Std*	*Mean*	*Std*	*Mean*	*Std*	*Mean*	*Std*
Austria	*whole*	*-35,6*	*24,9*	*15,1*	*6,7*	*12,0*	*2,9*	*-3,0*	*4,9*
	pre	*-25,3*	*23,7*	*15,1*	*4,0*	*12,0*	*1,7*	*-3,1*	*4,1*
	crisis	*-54,0*	*13,9*	*15,0*	*9,9*	*12,1*	*4,3*	*-2,9*	*6,1*
Belgium	*whole*	*-30,4*	*27,6*	*20,2*	*8,2*	*20,3*	*7,0*	*0,0*	*4,6*
	pre	*-17,6*	*25,1*	*22,8*	*5,4*	*20,7*	*4,1*	*-2,1*	*3,6*
	crisis	*-53,4*	*13,1*	*15,7*	*10,1*	*19,5*	*10,4*	*3,9*	*3,6*
France	*whole*	*-32,6*	*28,0*	*18,0*	*8,4*	*24,0*	*7,6*	*6,0*	*4,7*
	pre	*-20,5*	*27,1*	*19,9*	*7,3*	*24,7*	*6,5*	*4,8*	*5,0*
	crisis	*-54,4*	*11,9*	*14,7*	*9,4*	*22,7*	*9,2*	*8,0*	*3,4*
Germany	*whole*	*-50,6*	*24,0*	*0,0*	*0,0*	*11,9*	*3,5*	*11,9*	*3,5*
	pre	*-40,4*	*24,1*	*0,0*	*0,0*	*10,8*	*1,5*	*10,8*	*1,5*
	crisis	*-69,1*	*6,6*	*0,0*	*0,0*	*13,9*	*4,9*	*13,9*	*4,9*
Netherlands	*whole*	*-48,0*	*20,5*	*2,7*	*6,6*	*12,0*	*2,2*	*9,3*	*6,2*
	pre	*-39,2*	*20,3*	*1,1*	*7,4*	*11,9*	*1,1*	*10,7*	*7,2*
	crisis	*-63,7*	*6,9*	*5,4*	*3,4*	*12,2*	*3,4*	*6,9*	*2,2*
CORE	*whole*	*-32,9*	*20,5*	*9,3*	*3,8*	*13,4*	*3,6*	*4,0*	*1,8*
	pre	*-23,8*	*19,8*	*9,8*	*2,6*	*13,3*	*2,2*	*3,5*	*1,8*
	crisis	*-49,1*	*8,3*	*8,5*	*5,2*	*13,4*	*5,3*	*5,0*	*1,5*
Greece	*whole*	*159,2*	*128,9*	*209,8*	*108,4*	*250,5*	*121,9*	*40,7*	*32,1*
	pre	*218,8*	*120,0*	*259,2*	*100,1*	*309,0*	*107,1*	*49,8*	*34,0*
	crisis	*52,0*	*52,4*	*121,1*	*51,4*	*145,4*	*61,0*	*24,3*	*19,6*
Italy	*whole*	*97,7*	*77,1*	*148,3*	*64,1*	*16,4*	*13,8*	*16,4*	*13,8*
	pre	*129,5*	*73,2*	*169,9*	*64,1*	*181,3*	*56,2*	*11,4*	*13,0*
	crisis	*40,6*	*43,8*	*109,7*	*42,7*	*134,9*	*49,6*	*25,2*	*10,5*
Portugal	*whole*	*10,2*	*39,2*	*60,8*	*22,7*	*64,7*	*27,5*	*3,9*	*11,2*
	pre	*24,1*	*37,1*	*64,5*	*18,9*	*68,5*	*25,9*	*4,0*	*12,9*
	crisis	*-14,8*	*29,3*	*54,3*	*27,3*	*57,9*	*29,2*	*3,6*	*7,3*
Spain	*whole*	*0,7*	*29,6*	*51,3*	*15,6*	*58,4*	*22,0*	*7,1*	*12,3*
	pre	*11,8*	*28,0*	*52,2*	*13,8*	*55,7*	*17,2*	*3,5*	*10,7*
	crisis	*-19,4*	*20,3*	*49,7*	*18,4*	*63,3*	*28,3*	*13,6*	*12,4*
PERIPHERY	*whole*	*66,9*	*65,5*	*117,6*	*47,1*	*134,6*	*52,1*	*17,0*	*9,7*
	pre	*96,0*	*60,3*	*136,4*	*42,8*	*153,6*	*47,9*	*17,2*	*9,3*
	crisis	*14,6*	*35,7*	*83,7*	*34,4*	*100,4*	*41,5*	*16,7*	*10,6*

Table 9: Descriptive statistics of the data. Means and standard deviations of bond yields, bond spreads above the benchmark, CDS spreads and bases for 9 countries and the core and peripheral counties. Source: author's elaborations on Bloomberg and CMA data.

were almost unaffected. Nonetheless, CDS spreads could have had a role in the visible break around the pandemic declaration. Many studies have already tested the role of CDS in pricing the increased perceived default risk when sudden changes of market conditions occur[71]. However, since all the observations in this study are weekly, a precise estimation on the price-discovery process cannot be done. Consequently, I limit my work to the overall contribution of some explanatory factors on the basis, leaving the price-discovery analysis for future research.

Another important point of the empirical analysis is to understand the role of the ECB's purchases in the secondary markets: as aforementioned, bond spreads dropped in almost every country during the crisis, while CDS were more stable: this phenomenon suggests that bond yields may have been affected by a big investor like the ECB, that can directly influence bond yields and produce a temporary overpricing in the sovereign market, even if the default risk increases. While other papers have specifically assessed the role of central banks in bond and CDS markets during symmetric shocks[72], the impact of the PEPP on the basis is one of the main questions of this thesis.

3.2 Basis drivers

In this paragraph, I discuss which factors I decided to include in the analysis, how I built the appropriate proxies for the regression analysis, and some hypotheses on the expected sign of their coefficients on the basis.
The explanatory factors considered, summarized in Table 10, are:

- Counterparty risk: as mentioned before, even if the rules introduced after the 2008 financial crisis have reduced counterparty risk by introducing the Central Clearing Counterparties, some authors still include this factor as explanatory of the basis. This variable has been studied by Arora et al. (2012), who argue that since market participants reduce their counterparty risk by collateralizing their transactions, it

[71] In particular, Varga (2009) showed that CDS tend to exacerbate its fluctuations in periods of high volatility.
[72] See Carnazza & Liberati (2021).

should have little or no impact on the basis. However, especially during market turmoil and uncertainty, counterparty risk cannot be excluded from the analysis as the risk of more than one dealer defaulting could increase substantially.

I downloaded the CDS spread of some of the major dealers in the OTC markets[73] from CMA and I obtained a proxy for the common counterparty risk with a principal component analysis (PCA). The first principal component explained 81,6% of the total variance in the spreads, so I used this factor as a proxy for the counterparty risk across the dealers.

Since a high counterparty risk implies a lower credit protection for the buyers of CDS, I expect this variable to impact the basis negatively, as it also negatively impacts the CDS spreads.

- Bond market liquidity: this variable, which I proxied by taking the absolute value of the bid-ask spread in the benchmark yields taken from Bloomberg, should correlate negatively with the basis. In fact, a higher liquidity in the bond market (proxied by a low bid-ask spread) should in principle make cash bonds more appealing to investors, increasing bond prices relatively to CDS and thus increasing the basis.
- CDS-bond liquidity ratio: this measure, obtained from Bloomberg is similar to the previous one but should have an opposite impact on the basis. It is computed by taking the ratio of the bid-ask CDS spread and the bond liquidity measure. When this ratio is high, degree of liquidity the CDS markets is lower than in the bond markets, so the basis should increase. I chose to use the liquidity Ratio between CDS and bond instead of the original time series of CDS bid-ask spread because of stationarity issues.[74]
- EUR/USD exchange rate uncertainty: since most of the sovereign Eurozone CDS are quoted in dollars while bonds are quoted in Euros, I needed to include a proxy for the risk of devaluation in case of a credit event in the Eurozone in my model. As in Fontana and Scheicher (2015), I used as a proxy the CBOE Eurocurrency Volatility (EVZ) Index, which measures the market's expectation of 30-day volatility of the

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[73] The dealers considered are based on the 2010 ISDA Research note on the Concentration of OTC derivatives among Major dealers. They are Bank of America Securities LLC, Barclays Capital Inc, BNP Paribas Securities Corp., Citigroup Global Markets Inc, Credit Suisse Securities, Goldman, Sachs & Co., HSBC Securities (USA) Inc., J.P. Morgan Securities Inc., Morgan Stanley & Co. Incorporated, Bank of Scotland, Société Générale, UBS Group AG, Wells Fargo & Co.
Some dealers (as Nomura and Deutsche Bank) that are in the ISDA list have been excluded because of missing values in the CDS spreads for senior debt.

[74] See next paragraph for data adjustments.

EUR/USD exchange rate by applying the VIX methodology to options on the CurrencyShares Euro Trust (FXE). This index was available on Bloomberg on a weekly basis.

As discussed in paragraph 2.1.3.2, this variable should have a positive impact on the basis, as it makes CDS spreads more valuable to investors.

- Pandemic Emergency Purchase Programme (PEPP): as discussed in the previous paragraph, I expect that the ECB's purchases in the secondary markets played a role in increasing the basis, driving down bond yields, especially in peripheral countries. Although the ECB provides weekly updates of its net purchases within the Eurozone, I could not find a weekly historical breakdown of the ECB's purchases since the PEPP started. Nevertheless, since this information was available at a bimestrial frequency, I decided to interpolate the bimestrial data to obtain weekly observations[75]. This proxy should at least give information about the asymmetric impact of the ECB across the different sub-samples (core vs. periphery).
- PEPP announcements: to further explore the role of the ECB on the basis, I decided to include in my model some dummy variables that correspond to the dates of the first announcement of the PEPP and the following reinforcement announcements. While the previous variable (that tracks the actual purchases of the ECB), starts on April 4th, 2020, these dummies take value 1 from the announcement onwards, and zero before. The breakpoints are fixed on March 18th, 2020 (first announcements), June 4th, 2020 (first reinforcement) and December 10th, 2020[76].
- Financing costs: this factor is included in the model, as it aims to capture the difficulty for investors to finance the purchase of bonds and to enter a negative basis trade. As we already discussed, this cost does not affect CDS premia, because most of the CDS require little or no initial funding. Hence, a higher financing cost would diminish the demand for bonds and have a negative impact on the basis. As in Acharya (2007) and Arce et al. (2013), to proxy for the cost of funding faced by global intermediaries I used the spread between the 90-day US AA-rated commercial paper interest rate for financial companies and the 90-day US Treasury bill. This information was available on the FED's database[77].

[75] I assumed constant purchases each week.

[76] Source: ECB website.

[77] CPDR9AFC Index - GB3 Govt.

- Common volatility: a common volatility in the Eurozone could potentially influence the basis if the credit spread reacts differently to stock market changes. CDS could move more intensely than bond spreads when a crisis occur. I built this variable by taking the first principal component[78] obtained by the squared national stock indexes returns of the countries in my sample.
- Flight to quality: as my last explanatory variable, I built an indicator function that captured the "flight-to-quality" phenomena. A "flight-to-quality" is the decrease of demand for risky asset in favor of the safer ones during a period of market distress. As this event can be observed in the market and measured with the decrease in correlations between riskier and safer assets, I obtained from Bloomberg the time series of some risky assets[79] and computed the average returns of the safer and riskier assets. I then assigned value 1 to the indicator function when the risky asset returns decreased with the safe assets' yields and 0 otherwise.

  I expect this variable to explain the persistence of the positive basis in core countries and to have a negative influence on the peripheral countries bases.

Factor	*Abbreviation*	*Expected impact*
Counterparty risk	*CR*	*(-)*
Bond market liquidity	*Liq_bond*	*(-)*
CDS-bond liquidity ratio	*Liq_ratio*	*(+)*
EUR/USD exchange rate uncertainty	*Exchg*	*(+)*
Financing costs	*FC*	*(-)*
Pandemic Emergency Purchase Programme	*PEPP*	*(+)*
Common volatility	*CV*	*(+)*
Flight to quality indicator	*FTQ*	*(-)*
Dummy PEPP's first announcement	*PEPP_1*	*(+) (-)*
Dummy PEPP's first reinforcement	*PEPP_2*	*(+) (-)*
Dummy PEPP's second reinforcement	*PEPP_3*	*(+) (-)*

Table 10: Summary of the explanatory factors considered and the expected effects on the basis. Where both signs are present, the impact is uncertain or not unilateral. Source: author's elaboration.

[78] This variable explained 83,48% of the total variance of the stock indexes returns, so it proxies accurately the common volatility within the Eurozone.

[79] I considered two safe assets (the 10-year German bond and the 10-year Treasury bill) and two global indices (the Bloomberg Global High Yield Index and the MSCI World index) to proxy for the riskier assets.

3.3 Regression analysis

To study the impact of the variables considered on the basis, I divided the regression analysis in two parts: first, I carried out a time series analysis for each individual country using a series of regression models. Then, a Fama-MacBeth (1973) regression is applied on the different groups of countries to assess whether – as I expect - a cross-sectional approach is more meaningful in explaining the basis.

3.3.1 Structural break estimation

To set the empirical analysis in a rigorous way, I decided to test whether the division of the sample period was justified by the presence of a structural break in the time series.
To test the hypothesis of the presence of structural breaks, I first estimated a linear trend model of the form:

$$Y_t = \beta_0 + t\beta_1 + \varepsilon_t \,,$$

where β_0 is the intercept, β_1 is the linear trend coefficient and ε_t are the iid[80] model errors from a normal distribution with zero mean and unknown variance.
As discussed in the last paragraph, the break point is set on the 13th of March 2020. To validate the presence of a structural break around this date, I perform a Chow test on the time series of the bond yields, of the CDS spreads and on the basis.
As the null hypothesis of the test is the stability of the parameters of the separated regressions run before and after the break point, the structural break is validated whenever the null hypothesis is rejected, justifying the better explanatory power of the divided regressions with respect to the single regression model applied to the whole period.
Table 11 summarizes the result of the estimated test statistics, the p-values and the significance of each coefficient. The first 8 panels contain the individual test statistics for each country, while the last two the test statistics for the time series of the average basis for the core and peripheral countries.

[80] Independent and identically distributed.

	AT			*BE*		
	Bond	*CDS*	*Basis*	*Bond*	*CDS*	*Basis*
F-statistics	*32,56*	*81,16*	*19,56*	*22,58*	*74,258*	*28,8*
p-value	*1,33E-12*	*<2,2E-16*	*2,48E-08*	*2,27E-09*	*<2,2E-16*	*1,91E-11*
Significance	***	***	***	***	***	***
	FR			*NE*		
	Bond	*CDS*	*Basis*	*Bond*	*CDS*	*Basis*
F-statistics	*18,882*	*29,001*	*5,2122*	*23,421*	*124,05*	*13,185*
p-value	*4,30E-08*	*1,75E-11*	*0,006407*	*1,18E-09*	*<2,2E-16*	*4,98E-06*
Significance	***	***	***	***	***	***
	GR			*IT*		
	Bond	*CDS*	*Basis*	*Bond*	*CDS*	*Basis*
F-statistics	*45,655*	*5,2596*	*16,974*	*3,6948*	*17,084*	*29,374*
p-value	*2,22E-16*	*0,006128*	*2,05E-07*	*0,02698*	*1,87E-07*	*1,33E-11*
Significance	***	***	***	***	***	***
	PT			*SP*		
	Bond	*CDS*	*Basis*	*Bond*	*CDS*	*Basis*
F-statistics	*33,352*	*80,814*	*72,889*	*18,223*	*95,499*	*150,14*
p-value	*7,76E-13*	*<2,2E-16*	*<2,2E-16*	*7,35E-08*	*<2,2E-16*	*<2,2E-16*
Significance	***	***	***	***	***	***
	CORE			*PERIPHERY*		
	Bond	*CDS*	*Basis*	*Bond*	*CDS*	*Basis*
F-statistics	*30,465*	*70,39*	*45,316*	*17,81*	*20,401*	*27,943*
p-value	*6,01E-12*	*<2,2E-16*	*<2,2E-16*	*1,03E-07*	*1,27E-08*	*3,83E-11*
Significance	***	***	***	***	***	***

Table 11. Chow test estimation results. The estimation for core and peripheral counties is based on the average time series for the different groups of countries. The significance of the structural break is also confirmed for Germany, which is excluded for graphical reasons. The sample period goes form 02/03/2018 to 23/04/2021. Source: author's elaboration on Bloomberg and CMA data.

The results of the test show that the guess about the presence of a structural break around the date of the WHO's pandemic declaration was right. For each country, either in bond yields, CDS spreads and bases, the null hypothesis is rejected at any significance level. Therefore, I decided to split the empirical analysis in two parts, running different regression models before and during the crisis[81].

By doing that I could also indirectly study how the coefficient of my models were affected by the structural break.

[81] From now on, all the results will be split between the pre and during crisis period and displayed in separated panels.

3.3.2 Data adjustments

Before starting the regression analysis, I checked the stationarity of all the time series by means of an Augmented Dickey-Fuller test[82]. The test has this specification:

$$\Delta Y_t = \beta_0 + t\beta_1 + \gamma Y_{t-1} + \delta_1 \Delta Y_{t-1} + \cdots + \delta_{p-1}\Delta Y_{t-p+1} + \varepsilon_t ,$$

where the tested coefficient is γ. The more negative the test statistics is, the more the null hypothesis of non-stationarity is rejected. The auto-regressive order p for the test is set as:

$$p = trunc[(lenght(x) - 1)^{1/3}] .$$

I run the test on the time series of the bases for all the countries, and for all the explanatory variables in my models. As discussed before, the tests are run on two separated periods for each time series. The results, that are omitted for brevity reasons, showed that the basis behaved like a non-stationary variable in both periods for most of the countries. Regarding the explanatory variables, the only non-stationary one was "counterparty risk". Since non-stationarity violates one of the main assumptions of the regression analysis, I decided to take the first differences of all the time series and, therefore, to study the effect of the change in the explanatory variables on the changes in the basis. The analysis in changes should not affect the signs of the coefficients whatsoever.
With the same test specification, I tested the differenced time series and found that they are all stationary, so I decided to conduct the analysis in changes. Therefore, the general model specification for both the subperiods was:

$$\Delta Y_t = \beta_0 + \beta_1 \Delta Liq\_Ratio_t + \beta_2 \Delta Liq\_bond_t + \beta_3 \Delta CR_t + \beta_4 \Delta Exchg_t + \beta_5 \Delta FC_t + \beta_6 \Delta CV_t + \beta_7 \Delta FTQ_t + \varepsilon_t ,$$

where Y_t is the time series of the basis of each country[83], β_0 is the constant term and ε_t the iid error term.

[82] Dickey and Fuller (1979).
[83] The ECB's factors are left to the next paragraph as it started after the break point.

Another matter of concern when fitting multivariate regression models on time series is the correlation among the explanatory variables (called multicollinearity) that can lead to spurious regression, invalidating the model. Figure 6 displays a visual representation of the correlation matrices before and after the break.

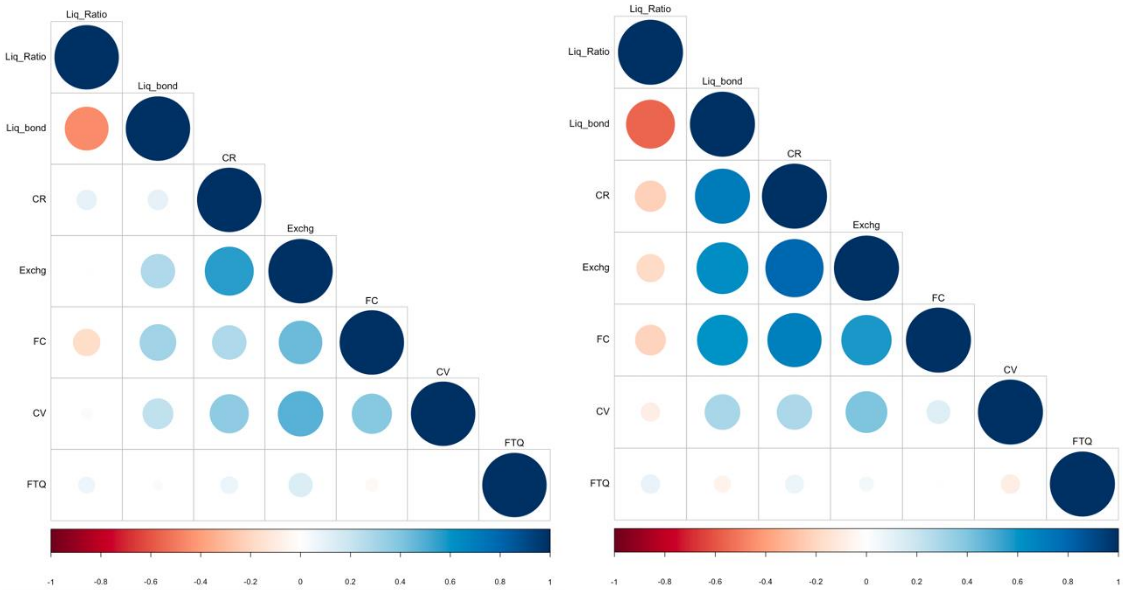

Figure 6: correlations among the coefficients. The left figure displays the correlations before the structural break, the right figure after the break. Observations are at a weekly frequency. The correlations are obtained as an average of the correlation matrices of all the countries in the sample. Source: author's elaboration on Bloomberg data.

Before the crisis, the correlations remained at tolerable levels. However, the only satisfying variable, that can be certainly considered independent from the others is the flight-to-quality indicator (with a maximum correlation at 0,14). The rest of the variables showed high correlations, especially after the break, and represented a concern for a multiple regression model. In particular, the exchange rate uncertainty was highly correlated with the proxy for counterparty risk and with financing cost. Moreover, the measure for bond illiquidity showed a significant increase in correlation with the proxies for counterparty risk, financing costs and exchange rate uncertainty, (with values above 0,4), which is quite intuitive during periods of market distress.

While the structural multicollinearity (that affects the bond illiquidity and the liquidity ratio) can be reduced, most of these co-movements were intrinsic in the data, and were direct consequences of economic relations behind these time series. Therefore, these behaviors must be taken into consideration when choosing the model specification.

3.3.3 Time series analysis

As discussed in the previous paragraph, the correlation matrices showed high levels of collinearity in the data. Therefore, in order to set the models in a correct specification and avoid the spurious regression, I decided to run a series of univariate regressions for each factor and for all the countries in the sample. Table 12 displays the estimated coefficient obtained. The reported coefficients are scaled by one standard deviation, centered, and adjusted for heteroskedasticity.

Before the crisis, even if most of the coefficients have signs which are consistent to my hypotheses, their high standard errors make them statistically unsignificant in explaining the basis. This resulted in a low explanatory power of the models before the crisis: for 7 countries of the sample in the pre-crisis period, the factors included in my model explained less than 10% of the total variation of the basis. The only remarkable exceptions were Belgium, where the adjusted R-squared reached 20% and Germany, where it was 42%. In those two countries, in the period before the break, some interesting results emerged: for Belgium, both the liquidity ratio coefficient and the bond market illiquidity coefficient are significant at a 5% significance level, and counterparty risk is significant at any confidence level. The signs of these 3 coefficients are all consistent with my expectations. Overall, in the period before the break the most influencing variable was counterparty risk. The negative impact of this variable on the basis is an interesting result as it goes counter to recent studies[84] that argued that, after of the introduction of the Clearing Counterparties, counterparty risk can be considered negligible. In this case, the rise in the CDS spreads of some of the most important dealers in OTC markets seem to have decreased the perceived quality of protection of CDS contracts, thus decreasing the basis. Another interesting result obtained before the crisis is the significance of the exchange rate uncertainty for Germany: the positive sign of this coefficient is presumably due to the additional currency hedging given by a USD-quoted CDS on a Euro-quoted bond. However, since in most of the countries this variable was non-significant, I deduce that the risk of euro depreciation in case of the default of one of the countries in the sample

[84] See Arora et al. (2012).

	AT	BE	FR	GE	NE	GR	IT	PT	SP
Constant	-0,02	-0,01	0,05	-0,04	0,25	-0,32	0,08	0,38	0,13
	(0.22)	(0.28)	(0.27)	(0.07)	(0.29)	(1.41)	(0.90)	(0.57)	(0.49)
Liq_Ratio	-0,56	-0.88 *	-0,04	0,00	-0,13	-0,52	0,00	-0,32	0,02
	(0.58)	(0.40)	(0.04)	(0.02)	(0.14)	(0.66)	(0.08)	(0.41)	(0.06)
Liq_bond	0,00	0.91 *	0,43	-0,05	0,17	-0,10	-0,77	-0,35	-0,13
	(0.14)	(0.39)	(0.88)	(0.28)	(0.53)	(0.48)	(1.84)	(0.76)	(1.51)
CR	-0,02	-0.07 ***	-0,03	-0.03 **	-0.05 **	0,07	-0,01	0,00	0,01
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.13)	(0.09)	(0.05)	(0.05)
FC	0,28	-0,17	-0,62	1,10	1,43	9,82	0,62	-2,24	-2,84
	(1.57)	(2.18)	(1.59)	(0.87)	(2.13)	(16.08)	(5.10)	(4.68)	(3.49)
CV	-29,45	-35,44	-44,61	-24,80	0,20	423,10	118,18	-136,83	-75,71
	(34.54)	(78.02)	(54.55)	(70.47)	(31.32)	(229.58)	(201.25)	(69.28)	(53.91)
Exchg	-0,03	-0,49	-0,38	0.41 **	-0,55	-1,05	-0,20	0,51	-0,43
	(0.35)	(0.42)	(0.39)	(0.16)	(0.43)	(3.03)	(1.70)	(1.02)	(1.07)
FTQ	0,19	-0,96	-0,39	-0,12	-0,45	-3,04	0,01	-1,20	-0,41
	(0.42)	(0.62)	(0.25)	(0.14)	(0.24)	(2.25)	(1.31)	(0.75)	(0.78)
N	105	105	105	105	105	105	105	105	105
Adj R^2	0,06	0,20	0,04	0,42	0,09	0,10	0,02	0,06	0,02

	AT	BE	FR	GE	NE	GR	IT	PT	SP
Constant	-0,17	-0,11	-0,41	0,12	-0,14	0,96	0,21	-0,11	0,28
	(0.33)	(0.42)	(0.42)	(0.15)	(0.29)	(1.70)	(0.82)	(0.86)	(0.97)
Liq_Ratio	-1,52	-0,12	0,12	0,05	0,02	-0,03	-0,47	0,26	-0,11
	(1.11)	(0.21)	(0.15)	(0.03)	(0.34)	(2.18)	(0.33)	(0.30)	(0.22)
Liq_bond	-0.89 *	0,96	0,46	-0,51	0,04	-0,52	-8.39 **	6,55	7,92
	(0.40)	(0.80)	(0.91)	(0.31)	(0.51)	(0.74)	(2.69)	(6.72)	(8.39)
CR	-0.05 **	0,03	0,03	0,02	0,02	-0,12	0,03	0,10	0,11
	(0.01)	(0.05)	(0.05)	(0.01)	(0.03)	(0.20)	(0.03)	(0.08)	(0.09)
FC	-0,30	3,74	4,70	0,53	2,53	-19,85	-1,30	4,88	5,56
	(2.77)	(9.06)	(9.51)	(2.74)	(5.01)	(28.76)	(4.58)	(15.30)	(17.56)
CV	56.23 *	-109,26	-120,02	-39.56 ***	-66,26	415,23	-73,37	-216,25	-242,15
	(24.30)	(125.02)	(123.66)	(5.06)	(65.15)	(548.85)	(185.63)	(179.06)	(185.22)
Exchg	-1.17 **	0,62	0,41	0,34	0,31	-3,61	-0,07	1,76	1,82
	(0.35)	(0.89)	(1.06)	(0.28)	(0.57)	(3.85)	(1.50)	(1.86)	(2.39)
FTQ	-0,48	-0.98 *	-0,73	0,30	-0,51	2,00	-0,60	-1,19	-1,51
	(0.43)	(0.44)	(0.41)	(0.20)	(0.35)	(1.81)	(1.33)	(0.87)	(1.11)
N	58	58	58	58	58	58	58	58	58
Adj R^2	0,41	0,52	0,60	0,44	0,40	0,57	0,26	0,48	0,41

*Standard errors are heteroskedasticity robust. *** p < 0.001; ** p < 0.01; * p < 0.05.*

Table 12: estimated coefficients for individual countries. The reported coefficients are scaled by one standard deviation, centered and robust to heteroskedasticity. Source: author's elaboration.

is considered rather low or inexistent, presumably because of the soundness of the Euro System as a whole.
Even if most of the estimated coefficients remained non-significant at the individual-country level, the general explanatory power of the models increased during the pandemic. As before the crisis, the illiquidity of the bond market had a negative impact on the basis, this time for Austria (estimated coefficient of -0.89 and a std. error of 0.40) and for Italy (estimated coefficient -8.39 and std. error of 2,69). For Austria, counterparty risk remained significant and with the expected sign.
What's interesting is the controversial impact on the basis for the EMU common volatility proxy, that increased the basis in Austria and decreased it in Germany. This seemingly discordant result may suggest a twofold effect of the stock market movements among different countries. In general, I expected this coefficient to be positive for core countries and negative for the peripheral countries. In the case of Germany, the rise in stock return's volatility has presumably decreased the perceived default risk for this solid country, causing the CDS spreads to fall more than the bond yields. For Austria, instead, the coefficient is in line with my hypotheses.

Overall, the results of the time series analysis are not so explanatory: even if some of the regressors certainly influenced the basis, most of them resulted to be non-significant at a country level. Nevertheless, since most of the proxies I built for the models are non-country specific, I expect them to be more significant at a cross-sectional level.

3.3.4 Cross-sectional analysis

As expected, the explanatory power of the individual regression models is quite low.
However, since of the main objectives of this thesis is to investigate whether there has been an asymmetric behavior of the basis between the core and peripheral countries, I carried out a cross-sectional analysis using the same risk factors used for the single-country time series analysis. As already discussed, since most of the factors already used are not country-specific, a cross-sectional analysis should give more information about their influence on the bases.
Moreover, to answer another research question of the thesis, I carried out an analysis of the ECB's PEPP impact on the basis by adding 4 factors to the previous specifications. These 4 proxies are particularly interesting for the objectives of this work as they measure

how the response to the pandemic influenced the divergence between CDS and bond spreads in the two groups of countries.

The model adopted is the Fama-MacBeth (1973) regression model with the following specification:

$$\Delta Y_{it} = \beta_0 + \beta_1 \Delta Liq\_Ratio_{it} + \beta_2 \Delta Liq\_bond_{it} + \beta_3 \Delta CR_t + \beta_4 \Delta Exchg_t + \beta_5 \Delta FC_t + \beta_6 \Delta CV_t + \beta_7 \Delta FTQ_t + \beta_8 \Delta PEPP_t + \beta_9 \Delta PEPP\_1_t + \beta_{10} \Delta PEPP\_2_t + \beta_{11} \Delta PEPP\_3_t + \varepsilon_{it}$$

where ΔY_{it} is the vector of the bases[85].

This procedure consists in an OLS[86] cross-sectional estimation of all the coefficients for each point in time. The overall coefficients are then obtained by taking the time series averages for each coefficient.

To control for the country-specific changes in the basis, I estimated the coefficients on the demeaned data, that is a convenient way to estimate fixed-effect coefficients rather than introducing a dummy for each country[87]. This adjustment should reduce the movement of the basis that are directly provoked by country-specific factors that are not included in the model. As for the time series analysis, I used nested or reduced models to avoid collinearity among the regressors. The estimated coefficients are reported in Table 13. As for the time series analysis, the coefficients are in basis points and the standard errors are heteroskedasticity adjusted.

As expected, the significance of the coefficients in explaining the cross-sectional changes in the basis increased with respect to the univariate time series analysis.

Before the break point, for the core countries, liquidity ratio, counterparty risk, exchange rate uncertainty and EMU common volatility were all significant in explaining the basis.

[85] Notice that all the variables are in changes, for the same reasons mentioned in paragraph 3.2.

[86] Ordinary Least Squares.

[87] Having only 59 observations after the break point, estimating many coefficients in the same model would have been rather unprecise.

	CORE			PERIPHERY		
	Estimate	*Std. error*	*Pr(>|t|)*	*Estimate*	*Std. error*	*Pr(>|t|)*
(Intercept)	*-0,0292*	*0,0478*	*0,5415*	*0,013*	*0,263*	*0,960*
Liquidity ratio	*-0,3940*	*0,2284*	*0,0845 .*	*-0,679*	*0,453*	*0,134*
Bond liquidity	*0,1395*	*0,2177*	*0,5214*	*-0,893*	*0,202*	*9,8 e-06 ******
Counterparty risk	*-0,0311*	*0,0175*	*0,07449 .*	*0,039*	*0,031*	*0,216*
Exchange rate uncertainty	*0,1391*	*0,0650*	*0,0323 **	*-0,719*	*0,734*	*0,327*
Financing costs	*1,2451*	*0,5797*	*0,0317 **	*2,382*	*4,308*	*0,580*
EMU common volatility	*-19,2967*	*9,7405*	*0,0476 **	*1,095*	*1,556*	*0,482*
Flight to quality indicator	*-0,0239*	*0,1499*	*0,8735*	*-0,321*	*0,617*	*0,603*
	Multiple R-squared: 0.11761			*Multiple R-squared: 0.075087*		

	Estimate	*Std. error*	*Pr(>|t|)*	*Estimate*	*Std. error*	*Pr(>|t|)*
(Intercept)	*0,0150*	*0,0751*	*0,8419*	*-0,3097*	*0,1928*	*0,1082*
Liquidity ratio	*0,3871*	*0,3636*	*0,2869*	*0,5065*	*0,1547*	*0,0011 ***
Bond liquidity	*0,0187*	*0,2186*	*0,9317*	*8,0273*	*5,0532*	*0,1122*
Counterparty risk	*-0,0165*	*0,0049*	*0,0008 ****	*0,0503*	*0,0434*	*0,2462*
Exchange rate uncertainty	*-0,0053*	*0,2262*	*0,9811*	*-0,9866*	*0,4530*	*0,0294 **
Financing costs	*0,7153*	*0,3414*	*0,0361 **	*-1,2021*	*0,3545*	*0,0007 ****
EMU common volatility	*3,7546*	*7,0691*	*0,5953*	*-41,9481*	*85,1807*	*0,6224*
PEPP net purchases	*-0,0036*	*0,0019*	*0,0620 .*	*0,0023*	*0,0014*	*0,0965 .*
PEPP D1	*10,8317*	*4,2378*	*0,0106 **	*23,9167*	*9,7901*	*0,015 **
PEPP D2	*-3,1764*	*0,9007*	*0,0004 ****	*-7,9633*	*3,6366*	*0,02854 **
PEPP D3	*0,1209*	*0,3765*	*0,7481*	*0,8875*	*0,4057*	*0,0287 **
Flight to quality indicator	*-0,1262*	*0,2275*	*0,5791*	*-1,1241*	*0,2644*	*2,115e-05 ****
	Multiple R-squared: 0.61489			*Multiple R-squared: 0.47586*		

*Standard errors are heteroskedasticity robust. *** p < 0.001; ** p < 0.01; * p < 0.05; . p < 0.1 .*

Table 13: Results of the Fama-MacBeth (1973) cross-sectional analysis. Panel 1 reports the coefficients for the pre-crisis period, going from 02/03/2018 to 06/03/2020, Panel 2 reports the estimated coefficients for the period going from 13/03/2020 to 23/04/2021. Observations are on a weekly basis. The standard errors are based on the Newey-West computations. Source: author's elaboration on Bloomberg and CMA databases.

However, the overall explanatory power of the model remains quite low (multiple R-squared of 0,12). The same holds for the peripheral countries, for which the model was able to explain only 7% of the total variance of the basis in the pre-crisis period. Moreover, for the peripheral countries, the only significant coefficient was the bond illiquidity measure (estimated coefficient of -0,893). This result is consistent with the

time series analysis and to my expectations, confirming the role of the bond market liquidity as a plausible friction for the misalignment in prices between CDS and bonds.
The results for the core countries in the pre-crisis period are somewhat more controversial, in the sense that, even though some coefficients have the expected signs (counterparty risk, exchange rate uncertainty), some others flip their sign. In particular, the positive sign for the financing cost proxy and the negative sign for the liquidity ratio run counter to my expectations. This result is probably due to some residual collinearity with other factors. In any case, for the core countries the basis remained at extremely low levels, especially before the crisis (see the last plot of Figure 5), and the overall significance of these coefficients is rather low. What's worth noting in the first panel of Table 13 is the negative ad significant sign of the EMU common volatility indicator for the core countries: as discussed in the previous paragraph, this result confirms the different reacting behavior between bonds and CDS after stock market movements, with the bond yields driving down the basis probably due to a "flight-to-safety" effect.
Moving to the second Panel of Table 13, the results become more interesting. The level of significance of the models increases dramatically during the pandemic, explaining 61,4% and 47,6% of the bases cross-sectional changes respectively for the core and peripheral countries.
In the former, after the break counterparty risk is significant at a 99% confidence level, and it decreased the basis. However, as for the pre-crisis period, even though the proxy for financing costs in core countries is only significant at a 5% level, it is positively related to the basis, which is in contrast with my expectations.
This factor has a different impact on the cross-sectional variations of the basis in the peripheral countries, where it has a negative sign (estimated coefficient -1,2021, std. error 0,3545) and a high significance. This means that the difficulty in funding the purchase of bonds has prevented arbitrageurs from entering in negative basis trades[88].

Regarding the flight-to-quality indicator, it is significant only after the break and for peripheral countries, with a negative effect on the basis. I deduce that, after the pandemic declaration, most of the investors switched their positions from risky assets to safer assets, driving the peripheral countries bond spreads above the CDS spreads.

[88] Even if most of the times the basis remained positive, some negative basis episodes emerged in peripheral countries after the break (see Figure 5).

The last research question of this thesis regards the impact of the ECB's interventions to face the pandemic.

The estimated coefficients for the cross-sectional effect of the PEPP on the bases (displayed in the second panel of Table 13) were all significant, with the only exception being the dummy for the second reinforcement announcement for the core countries.

The ECB net purchases had a small but significant effect both in core and peripheral countries. However, the sign of the coefficient flips from negative (core) to positive (periphery), indicating that the ECB may have had a role in the divergence of the basis between the core and peripheral countries. The net purchases in peripheral countries have certainly contributed to lowering the bond spreads, widening the basis.

In addition to this interesting result, I found a strong significance of the dummies relative to the first PEPP announcement and of the first reinforcement announcement. In fact, the PEPP's announcements seem to have influenced the basis more than the actual purchases by the ECB. In both the groups of countries, the first announcement of the PEPP increased the basis, especially in the peripheral countries, while the first reinforcement announcement had a negative effect.

My interpretation is that the PEPP announcements were followed by a quick reaction in the bond and CDS markets, that anticipated the actual purchases of bond by the ECB and moved the basis upwards (first PEPP announcement) and downwards (first reinforcement announcement).

In general, I can conclude that the ECB played an important role in easing the tensions in the bond market after the pandemic declaration and that it influenced the basis. Moreover, the most significant movements were induced by the PEPP announcements rather than by the actual bond purchases in the secondary markets by the ECB.

Final remarks

In this thesis I discussed the similarities and differences between the CDS market and the cash bond market. After a brief introduction on the world of credit derivatives, I presented the main features of the CDS market, the functioning of CDS contracts and their pricing. Then, I described the theoretical equilibrium condition that links CDS and bond spreads and the methodology used for the basis computation.

In the empirical analysis, I computed the CDS-bond bases for a sample of 9 Eurozone countries, dividing them in “core” and “peripheral” countries according to their public finances.

Since one of the objectives of this work was to study whether the Covid-19 pandemic outbreak have had an influence on the bases, I tested the hypothesis of the presence of a structural break around the date of the WHO’s pandemic declaration (March 11th, 2020) and found that the structural break is significant for the CDS, the bond yields and the CDS-bond basis of all the countries in the sample.

This first result allows me to split the analysis between "pre-crisis" period (from 02/03/2018) to 06/03/2020) and "during-crisis" period (from 13/03/2020 to 28/04/2021). Overall, in the sample, the basis remained at relatively low levels, especially in core countries, where it never exceeded 10 basis points on average. For peripheral countries, even though it did not reach the levels documented by past literature during the sovereign debt crisis in 2011-2012, the basis deviated consistently from zero, more often in the positive field.

To assess which factors caused these deviations, I considered a set of possible drivers of the basis: some of them (such as bond illiquidity, counterparty risk and exchange rate uncertainty) had already been used in the literature, while some others (like the PEPP net purchases, and the dummies for the PEPP announcements) were newly considered as they directly measure the impact on the basis of the ECB's responses to face the pandemic.

In the first part of the empirical analysis, I carried out an individual time series analysis running a series of regressions for each country in the sample.

Since most of the explanatory variables were not country-specific, the regression models showed little explanatory power. However, I found some interesting significances in the estimated coefficients.

In the second part of the analysis, I used a cross-sectional approach for exploring the basis in the core and peripheral countries. Some of the results of the Fama-MacBeth (1973) cross-sectional regression were particularly relevant.: (i) counterparty risk, that has been considered negligible in previous papers, played a role in decreasing the basis, meaning that CDS spreads have been diminished by an increased CDS spread of the major OTC dealers; (ii) liquidity frictions in the bond and CDS markets affected the basis accordingly to the initial hypothesis and the bond illiquidity was the only significant coefficient before the structural break for peripheral countries, explaining alone 7% of the basis; (iii) funding frictions were significant and had a negative impact on the basis of peripheral countries during the crisis, meaning that the high funding rates for the repurchase agreements prevented the arbitrageurs from speculating on negative basis episodes; (iv) the flight to quality indicator was significant and negatively affected the basis on peripheral countries, probably as a consequence of the increase in bond spreads during the market turmoil arisen by the virus.

The last part of the cross-sectional analysis explored the role of the ECB's PEPP on the CDS-bond basis. In this case, also some relevant results emerged: the ECB's net purchases played an active role in making the basis of the core and peripheral countries to diverge. However, the PEPP's announcements had a more significant role in moving the basis than the actual purchases in the bond market, meaning that the market has probably anticipated the overpricing induced by the ECB in the bond market.

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