UNIVERSITÉ DE LIMOGES

École Doctorale Gouvernance des Institutions et des Organisations

Faculté de Droit et des Sciences Économiques

Laboratoire d'Analyse et de Prospective Economiques (LAPE) – UR 13335

Essays on the Informative Content of Regulatory Banking Stress Tests

Thèse

Pour obtenir le grade de

Docteur de l'Université de Limoges

Discipline / Spécialité : **Sciences Économiques**

Présentée et soutenue publiquement par

Amavi Signon Selom AGBODJI

Limoges, le 07 Novembre 2022

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To the loving memory of my dear sister Ayoko,
To the loving memory of my grand-Mother Suzanne,
I hope you will be smiling on this day. I hope I made you proud.

To my father and my mother,
None of this would have been possible without your sacrifices, encouragement, and endless support.

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SUMMARY

General Introduction

The last fifteen years have shown, once again, the strong link between the financial health of banking institutions and economic activity. Indeed, the Global Financial Crisis (GFC) of 2007–2008, the most severe since the Great Depression of 1929, triggered a Great Recession which led to a significant decline in economic activity for several quarters, especially in developed countries. This decline was mainly materialized by a sharp drop in real GDP, real income, industrial production, and a sharp increase in employment, among others. As a consequence, with the aim of preventing future financial crisis episodes and thereby avoiding their effects and costs (Kroszner *et al.*, 2007, and Dell'Ariccia *et al.*, 2008), the regulation and supervision of banks have been significantly strengthened to account for the new challenges highlighted by the GFC. It is within this framework that several ameliorations and fundamental changes have been made to bank stress testing, which is an important risk management tool used by banks as part of their internal risk management, and which is required by supervisors through the Basel II capital adequacy framework. Supplementing other risk management approaches and measures, it alerts bank management to unexpected adverse outcomes arising from a wide range of risks and provides an indication of the appropriate level of capital necessary to endure deteriorating economic conditions (Basel Committee on Banking Supervision, 2009).

However, as pointed out by the Bank for International Settlements (2009), there were several weaknesses in stress testing practices employed prior to the start of the GFC, which were revealed by the latter. First, since most of the banks did not have a comprehensive internal stress testing program that took into account the correlations between different positions and risk types, it was almost not possible to identify correlated tail exposures and risk concentrations across the bank. In other words, banks did not perform stress tests that took a comprehensive firm-wide perspective across risks and different books (trading book and banking book), but ran separate stress tests for particular portfolios or risks, with limited or no firm-level integration. As a result, they did not have a comprehensive view across credit, market and liquidity risks of their various businesses. Second, most internal stress testing were not designed to capture the extreme market events that were experienced during the GFC since most of banks generally applied only moderate scenarios, either in terms of severity or duration. In addition, as scenarios were designed based on significant market events experienced in the past, such internal stress tests were not able to capture risks in new products that have been at the center of the crisis. Third, specific risks and products were not taken into account or were not covered in sufficient details by banks' internal stress testing (among others, securitization risk, counterparty credit risk, contingent risks, and funding liquidity risk). Furthermore, these weaknesses are even more aggravated if we consider the banking system as a whole, since the internal stress testing programs are not uniform across banks. Their frameworks, scenarios, and objectives are aligned with each bank's specific risk appetite and risk management, thus making it almost impossible to estimate correctly the impact of unexpected deteriorating economic conditions on the stability of the whole banking system.

To fill these gaps laid bare by the GFC, and strengthen their supervisory practices, supervisors and macroprudential authorities introduce the regulatory banking stress test in order to better identify the underlying risks of regulated banks, and better detect potentially fatal weaknesses of banks that may threaten the orderly functioning and the stability of the banking system. While banks' internal stress tests are based on scenarios tailor-made for their respective circumstances, regulatory stress tests are carried out with a common set of tools, including common and consistent scenarios, common key assumptions, a common methodology which not only defines how tested banks should calculate the impact of the common scenario in a bottom-up fashion[1], but also sets constraints for their calculation.

A regulatory stress testing exercise is a scenario-based supervision tool used by banking authorities to assess and analyze the robustness of participating banks, individually and as a whole. In the beginning, it was considered as a crisis management tool since it was carried out in the aftermath of the GFC in an attempt to restore the confidence of market participants in the banking system. More precisely, regulatory stress tests were initially performed in order to strengthen the balance sheets of tested banks after repairing the identified problems, through remedial actions.

[1] With the bottom-up approach, banks generate their stress test projections using their own internal models, the advantage being that the exercise itself requires banks to invest in their risk management capabilities.

The aim was to assure market participants that after the implementation of the corrective actions, banks will be soundly capitalized as well as the banking system.

> *" The loss of confidence we have seen in some banking institutions has arisen not only because market participants expect the future loss rates on many banking assets to be high, but because they also perceive the range of uncertainty surrounding estimated loss rates as being unusually wide. The capital assessment program was designed to reduce this uncertainty by conducting a stringent, forward-looking assessment of prospective losses at major banking organizations. The objective was to identify the extent to which each of the 19 firms is vulnerable today to a weaker-than-expected economy in the future, and to measure how much of an additional capital buffer, if any, each firm would need to establish now to withstand the potential losses in more-adverse economic conditions."*
>
> Speech by Mr **Ben S. Bernanke**, Chairman of the Board of Governors of the US Federal Reserve system, at the Federal Reserve Bank of Atlanta 2009 Financial Markets Conference, Jekyll Island, Georgia, 11 May 2009.

However, due to their effectiveness (Hirtle *et al.*, 2009; Beltratti, 2011; Petrella and Resti, 2013; and Morgan *et al.*, 2014), regulatory stress tests have continued to be performed during the post-crisis period and are now formally established as an integral part of the banking supervisory toolkit. Nevertheless, it should be noted that it is not a substitute for banks' internal stress testing. Overall, these supervisory exercises assess (individually and as a whole) the soundness of participating financial institutions by testing their resilience to different forward-looking macroeconomic scenarios. In general, one can distinguish (i) a *baseline* scenario based on the most recent macroeconomic projections and (ii) an *adverse* scenario. The latter is an extreme but plausible "dark" scenario that simulates severe crisis situations, characterized by a deep recession at the national and global levels, harmful financial situations, a very high unemployment rate, etc. The objective is to ensure that the participating institutions have sufficient financial strength to absorb losses and to remain solvent and strongly capitalized, even in a distressed economic environment. Both scenarios are designed over three different time horizons (1-year, 2-year, and 3-year) and the financial strength of tested banks is assessed at the level of each horizon. In the end, banks that are identified as weak, or not robust enough, are then subject to corrective actions.

Another major characteristic of a regulatory stress test, that further differentiates it from banks' internal stress testing, is its level of transparency. At the end of each exercise, and in an attempt to reduce the uncertainty of market participants about tested banks (and thus reduce banking opacity), outcomes are publicly disclosed by supervisors as well as each tested bank's financial data. The disclosed outcomes consist of granular and consistent information on a bank-by-bank level illustrating, in details, how banks are affected by common shocks. In other words, the released stress test outcomes consist of a set of data that reflects, in a very detailed way, the evolution of the situation of each participating bank throughout the forward-looking scenarios, over the different time horizons. More precisely, these data highlight the evolution of banks' exposures, solvency, capital composition, market risk, credit risk, counterparty risk, liquidity risk, and operational risk, among others, thus allowing investors, analysts and other market participants to develop an informed view not only on the financial health and the resilience of tested banks, but also on the soundness of the banking system. This ultimately contributes to strengthen market confidence and market discipline.

The introduction of this new supervision tool has given rise to a new stream of literature which studies the informative value of the latter, most of the contributions being of an empirical nature. Several empirical works have indeed been performed in order to evaluate the informative content of the disclosed results of regulatory stress tests (among others, Petrella and Resti, 2013; Morgan *et al.*, 2014; Carboni *et al.*, 2017; Flannery *et al.*, 2017; Georgescu *et al.*, 2017; Ahnert *et al.*, 2018; Fernandes *et al.*, 2020). In most cases, these papers investigate whether there are any abnormal movements in the tested banks' (stock) prices and (CDS or bond) spreads, around the disclosure date. These abnormal movements are assumed to be caused by the fact that after the disclosure of results, market participants incorporate the information provided into the stock prices, bond spreads and CDS spreads of tested banks. Then, if they deem this information new, significant, and relevant, these prices and spreads should experience abnormal movements, thus proving the existence of an informative content in the disclosed results.

However, these previous papers have found mixed evidence of whether or not tested banks' (stock) prices and (CDS or bond) spreads experience significant abnormal movements at the disclosure. Some studies report statistically significant abnormal returns (stock or CDS spreads) on some disclosure event dates, but not on others (Candelon and Sy, 2015; Neretina *et al.*, 2015; Georgescu *et al.*, 2017, and Ahnert *et al.*, 2018). Considering a same disclosure, some studies report statistically significant abnormal CDS spreads returns, but non-significant abnormal stock returns (Neretina *et al.*, 2015). Also considering a same disclosure, some studies report statistically significant abnormal returns (stock or CDS spreads) while others do not (Morgan *et al.*, 2014 and Neretina *et al.*, 2015). To at least some extent, these varied and mixed findings may be explained by two main factors. First, the use of instruments (in the empirical investigations) which, due to their characteristics, highlight only part of the market reaction and which, therefore, do not make it possible to highlight and examine the entire informative content of stress tests. Second, these mixed findings reflect the failure to take account of the intrinsic temporality of stress testing exercises. Previous papers analyze the latter's informative value, exploring various financial markets without taking into account the fact that the information provided has different temporalities, as it is provided for each time horizon of each scenario. However, taking into account this temporality may be fundamental in highlighting and examining the tests' informative content.

To highlight and study the informative content of regulatory stress testing exercises, an appropriate instrument to use is the Credit Default Swap (CDS). It is a fixed income derivative instrument that allows a protection buyer to purchase insurance against a contingent "credit event" on an underlying reference entity, by making an annual payment (which can be divided into quarterly or semi-annual installments) to the protection seller over the life of the contract (Augustin *et al.*, 2014). This contract's life is generally referred to as the maturity of the CDS while the CDS spread (or CDS premium) corresponds to the annual amount paid to the protection seller, expressed (in basis points) as a proportion of the notional value of the contract. The standard contract specifies all the obligations and rights of the parties as well as key definitions, such as which situations constitute a "credit event"[2] (i.e. a default by the reference entity) and how a default can be verified (Bomfim, 2022).

[2] CDS contracts generally allow for the following types of default events: bankruptcy, failure to pay, debt moratorium, debt repudiation, restructuring of debt, acceleration or default.

The most cited CDS valuation model is the Hull and White (2000) model, in which the premium for a $1 notional value CDS is[3]:

$$\text{CDS premium} = \frac{\int_0^T [1 - \hat{\mathrm{R}} - A(t)\hat{\mathrm{R}}]q(t)v(t)dt}{\int_0^T q(t)[\mu(\mathrm{t}) + e(t)]dt + \pi\mu(\mathrm{T})}$$

The CDS spread therefore increases with the probability of default of the underlying reference entity, and the life T of the contract. For a given maturity, the greater the default risk, the higher the spread of CDS. In view of the above, CDS spread appears to be a relatively pure pricing of the default risk of the underlying entity (Zhang *et al.*, 2009), over different horizons since there are several maturities of CDS including the 6-month, 1-year, 2-year, 3-year, 4-year, 5-year, 7-year and 10-year maturity[4].

As a result, we consider that CDSs may be the most appropriate instruments to use for the following reason. On the one hand, at the release of stress test results, the information provided clearly highlights the evolution of the participating banks' financial health throughout an "anticipated" future (forward-looking *baseline* scenario) and a plausible crisis situation (forward-looking *adverse* scenario), over different time horizons (1-year, 2-year, and 3-year). In other words, stress tests provide to market participants new information on whether or not tested banks have sufficient financial strength to absorb losses and to remain strongly solvent (thus avoiding default), even in a distressed economic environment and considering different time horizons. On the other hand, CDS reflects the risk of default associated with the same bank, but at different maturities (horizons). Thus, the information provided over different horizons appears to be what CDSs reflect over different horizons, suggesting the consideration of CDS spreads of different maturities to examine the informative value of stress tests.

[3] **T** is the life of credit default swap; **q(t)** is the risk-neutral default probability density at time t; $\hat{\mathbf{R}}$ is the expected recovery rate on the reference obligation in a risk-neutral world, assumed to be independent of the time of the default and the same as the recovery rate on the bonds used to calculate q(t); **μ(t)** is the present value of payments at the rate of $1 per year on payment dates between time zero and time t; **e(t)** is the present value of an accrual payment at time t equal to t – t* where t* is the payment date immediately preceding time t; $\boldsymbol{v}$**(t)** is the present value of $1 received at time t; **π** is the risk-neutral probability of no credit event during the life of the swap; and **A(t)**: accrued interest on the reference obligation at time t as a percent of face value.

[4] The CDS market offers a unique opportunity because of the ability to contemporaneously observe multiple instruments that measure the risk associated with the same firm, but at different horizons (Lok and Richardson, 2011).

Another possibility is to use tested banks' bonds, which also have several maturities. But, CDS instruments have major advantages over bonds. First, unlike bond spread, CDS spread is a relatively pure pricing of the default risk of the underlying entity (Zhang *et al.*, 2009). Longstaff *et al.* (2005), for example, show that a large proportion of bond spreads are determined by liquidity factors, which do not necessarily reflect the default risk of the underlying entity. Second, CDS spreads are directly observable unlike bond spreads which have to be calculated using a benchmark risk-free yield curve (Ericsson *et al.*, 2006; Longstaff *et al.*, 2005). But, as evidenced by Houweling and Vorst (2005), the choice of the risk-free reference asset may be problematic. Third, CDS spreads appear to react more accurately and rapidly to new information regarding the underlying reference entity compared to bond spreads, especially in the short run (Blanco *et al.*, 2005). Put differently, CDSs lead the bond market in price discovery, which is a key advantage. According to Zhang *et al.* (2009), this could be partly attributed to the fact that CDSs are unfunded and do not face short-sale restrictions. This may also be due to important non-default components in bond spreads that obscure the impact of changes in the underlying entity's credit quality (Ericsson *et al.*, 2006). Fourth, another important advantage of using CDS data compared to bond data is that maturities of the CDS contracts are strictly standardized (they are the same across banks) and fixed over time, unlike bond contracts' maturities which are not uniform across banks and vary significantly over time (Han and Zhou, 2015). The existence of different standardized maturities is also one of the main advantages of CDSs, compared to stocks whose prices only indicate the current value (risk) of the reference entity. Also, compared to stocks, CDSs better reflect the default risk of the underlying entity. All these advantages further support the consideration of CDSs as instruments, rather than stocks or bonds.

Previous papers that examine the informative content of regulatory stress tests consider the stock value and bond spreads of tested banks (among others, Petrella and Resti, 2013; Daouda Dala *et al.*, 2020; and Daouda Dala, 2021). Some of them also consider, in addition, CDS spreads but to carry out their empirical analysis, they only use the 5-year maturity contracts (among others, Morgan *et al.*, 2014; Neretina *et al.*, 2014; Flannery *et al.*, 2017; Georgescu *et al.*, 2017; and Ahnert *et al.*, 2018).

In light of the above, this thesis addresses the following questions. CDSs being the appropriate instruments to apprehend the financial strength of banking institutions and appreciate the risk of default associated with the same institution, but at different maturities (horizons), which maturity(ies) should be considered to proxy for this bank default risk? Then, is the exclusive use of 5-year maturity CDS spreads sufficient to entirely appreciate the reaction of market participants to the disclosure of stress test results? Is it sufficient to fully evaluate the informative content of stress test results? Finally, since the *baseline* and the *adverse* forward-looking scenarios are not designed and elaborated in the same way, do the outcomes of each provide new and valuable information to market participants? And if so, is their informative content identical or not?

This thesis therefore aims to contribute to the stream of the literature on regulatory stress tests by empirically examining these issues, in three chapters. It aims to go further than the existing literature by exploring a more complete and refined analysis of the reaction of market participants following the disclosure of stress test results, and a more thorough and exhaustive examination of the determinants of this reaction, after studying the main instruments used, namely CDSs. It consists of three empirical papers, each one being represented by a chapter. Although these three papers are related to each other by their issues (especially the second and third papers), they use different empirical methodologies in their investigations. Also, each paper is self-contained and can be read individually. In the following, we briefly present for each, the motivations, the research questions, and the contributions.

The recent literature has extensively used credit default swaps, especially as a proxy of default risk and systematically considers the (spreads of the) 5-year CDS maturity, arguing that it is generally considered to be the most liquid segment of the market. However, very little is known about the CDS maturity that should be considered to proxy for the default risk of a bank. As highlighted by Ball and Cuny (2020), the term structure of a bank CDS spreads is a function of two components of market participants' uncertainty about the financial health of this bank: the uncertainty due to the imperfection of available information (first component) and the uncertainty about the occurrence of unpredictable economic shocks that will affect the bank's financial health (second component). These two components offer different implications for the bank probability of default depending on the horizon, and, thus, for the magnitude of the bank CDS spreads depending on the maturity. More precisely, a change in the market participants' uncertainty would not have the same impact on the bank CDS spreads. This impact would differ according to the maturity of the CDS contract and on whether it is a change in the first or the second component, or both. This therefore suggests that the spread of CDS, which is a relatively pure pricing of bank default risk, does not reflect the same aspect of this bank default risk depending on the maturity of the CDS contract. As a result, **Chapter 1** questions whether the 5-year maturity that is systematically chosen by the literature is the one that should be considered to proxy for the default risk of a bank. Or, is the sole consideration of the 5-year maturity sufficient? Is there one or several maturities of CDS that might contain or summarize all the information available on the default risk of a bank? In an attempt to answer these questions, we investigate if there is a CDS maturity that is representative of all others. In other words, we investigate if there is a maturity of CDS whose spread variations illustrate or summarize that of all the other maturities. For this purpose, we empirically examine how the spreads of the different CDS maturities relate to each other, and how does a shock to one of the maturities influence the others. We use a vector autoregressive (VAR) approach on a panel dataset of 49 European banks, over the 2010-2019 period, on a weekly basis. As the 5-year CDS maturity contracts are generally considered in the literature as the most liquid compared to the other maturities' contracts, before estimating our model, we first focus on the liquidity of all CDS contracts. We analyze the liquidity of CDS spreads of each maturity, using the data available to us.

Our results show that the difference between the maturities of CDS in terms of liquidity has decreased significantly over time since the GFC, until it disappears over the past decade. Also, our results suggest that the 5-year CDS maturity may not be representative of all the others. By contrast, the dynamics in the three shortest CDS maturities (the 6-month, 1-year and 2-year maturities) might be useful to consider in order to get an overall representation of the dynamics of all the maturities. Finally, our results confirm that a simultaneous shock to the two components of market participants' uncertainty has not the same impact on CDS spreads, depending on the maturity of the CDS contract. This last finding has some important implications. By disclosing the stress tests' results, banking authorities attempt precisely to reduce these two components of market participants' uncertainty. In other terms, in addition to improving the quality and quantity of information available on tested banks' situation (thus reducing the first component), the disclosure of stress test results also provides valuable information on the ability of these latter to absorb losses and to remain strongly capitalized, even in a difficult economic environment (thus reducing the second component). We therefore have a simultaneous shock to the two components of uncertainty and according to our results, this would not have the same impact on the spreads of the different maturities of CDS. This is an important finding since it seriously questions the sole use by the literature of the 5-year maturity CDS spreads when evaluating the informative content of regulatory stress tests. The next chapter further explores this issue.

Chapter 2, based on Agbodji *et al.* (2021), questions whether the sole use of the 5-year maturity is sufficient to entirely measure the reaction of market participants and fully evaluate the informative content of stress test results. In addition, insofar as stress tests are performed on short-term forward-looking scenarios (time horizon of 1, 2, and 3-year), and since the disclosed results (on participating banks' resilience and financial strength under the scenarios) only cover these short-term horizons, it can be expected that information provided should be better incorporated into CDS spreads whose maturities are less than or equal to 3 years, compared to CDS spreads of the remaining maturities (including the 5-year). This makes the sole use of the 5-year maturity even more questionable. Based on ten regulatory stress tests carried out in Europe and in the US, from 2009 to 2017, this chapter extensively analyzes the response of market participants to the disclosure of stress test results considering each of the eight maturities of CDS. The empirical results show that the market reaction differs substantially depending on the maturity of the CDS contract. As a consequence, we support that only using the 5-year maturity CDS spreads is not sufficient because it leads to an incomplete and partial analysis of the reaction of market participants. This, in turn, can lead to misinterpretations of the informative content of stress test results, and therefore, an incorrect appreciation of the effectiveness and informative value of regulatory stress testing exercises.

Chapter 3 aims to go further by studying the determinants of the reaction of market participants. Since the *baseline* and the *adverse* forward-looking scenarios are not designed and elaborated in the same way, this chapter considers distinctly the disclosed outcomes of both in order to examine whether each explains the abnormal movements in the CDS premium following the disclosure (i.e. the market reaction). Is their informative content identical or not, taking into account the different time horizons of scenarios? Further, as the market reaction differs substantially depending on the CDS maturity, are stress test outcomes that explain this reaction also different depending on the maturity of the CDS contract? Based on EU-wide stress tests conducted by the European Banking Authority, we find that in times of panic, market participants seem to derive new and relevant information from outcomes of both scenarios (especially the *adverse* ones). But, in times of calm, only the *baseline* scenario outcomes seem to provide them with such information, which mainly concerns investors who have a short-term horizon. Indeed, we show that the disclosed outcomes that explain the market reaction is not the same from one CDS maturity to another. It differs depending on whether one considers the short-term horizon (6-month, 1-year, and 2-year CDS maturity) which seems to be the most provided in informational content, or the medium or long-term horizon.

The remainder of the thesis is organized as follows. We start by presenting Chapter 1 ("*CDS Spreads as a Proxy for Bank Default Risk: Do All Maturities Bear the Same Information?*"), then Chapter 2 ("*Do CDS Maturities Matter in the Evaluation of the Informative Content of Regulatory Banking Stress Tests? Evidence from European and US stress tests*"), and lastly Chapter 3 ("*Time horizons, Baseline and Adverse Scenarios: A New Assessment of the Informative Content of Regulatory Banking Stress Tests*"). Finally, we discuss in a concluding chapter the contributions and implications of our findings.

CHAPTER 1 | CDS Spreads as a Proxy for Bank Default Risk: Do All Maturities Bear the Same Information?*

* This chapter draws from the working paper "CDS Spreads as a Proxy for Bank Default Risk: Do All Maturities Bear the Same Information?". I am grateful to my supervisors, Dr. Emmanuelle NYS and Prof. Alain SAUVIAT, for their advice, guidance, and suggestions during the development of this work. I have also received very constructive comments and advice from Dr. Foly S. Ananou.

1.1. Introduction

A Credit Default Swap (CDS) is a fixed income derivative instrument that allows a protection buyer to purchase insurance against a contingent "credit event" on an underlying reference entity, by paying an annuity premium (which can be paid in quarterly or semi-annual installments) to the protection seller over the life of the contract (Augustin *et al.*, 2014). This contract's life is generally referred to as the maturity of the CDS while the CDS spread corresponds to the annuity premium expressed (in basis points) as a proportion of the notional value of the contract. The standard contract specifies all the obligations and rights of the parties as well as key definitions, such as which situations constitute a "credit event"[5] (i.e. a default by the reference entity) and how a default can be verified (Bomfim, 2022). Credit default swaps are by far the most popular and the main credit derivatives product in terms of notional amount outstanding (Bomfim, 2016). Their transactions which are well standardized by the International Swaps and Derivatives Association (ISDA)[6] are done over-the-counter, and more than 99% of these contracts have a maturity less than or equal to 10 years[7] (Abad *et al.*, 2016).

However, although a body of the literature has been dedicated to empirically study credit default swaps[8] thanks to the rapid growth of the CDS market over the last two decades, there is a number of questions that remain unanswered. This paper aims to address one of these issues. The recent literature has extensively used credit default

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[5] CDS contracts generally allow for the following types of default events: bankruptcy, failure to pay, debt moratorium, debt repudiation, restructuring of debt, acceleration or default.

[6] The most commonly used agreement in CDS transactions is the ISDA Master Agreement. In March 2009, the latter is significantly improved since ISDA introduced a number of important changes in its Credit Derivatives Determinations Committees and Auction Settlement CDS Protocol, which increase considerably standardization of the market.

[7] For example, considering the first half of 2019 (so just before the Covid crisis), single-name contracts with maturities less than or equal to 1 year represent 24,5% of the total notional amount insured (essentially 1-year maturity contracts) while contracts with maturities beyond five years represent 8,4% of this total (essentially, 7-year and 10-year maturity contracts). Thus, 67,11% of the total notional amount insured relates to the maturities of 2-year, 3-year, 4-year and 5-year (Bank for International Settlements, 2021).
Asset-backed and mortgage-backed securities represent the class of underlying entities for which the distribution of maturities is concentrated in maturities in excess of 10 years, and their markets account for only around 0.9% of the total notional amount insured (Abad *et al.*, 2016).

[8] Among others, Chen *et al.*, 2008; Ericsson *et al.*, 2009; Zhang *et al.*, 2009; Corò *et al.*, 2013; Annaert *et al.*, 2013; Hasan *et al.*, 2014; Galil *et al.*, 2014; Han and Zhou, 2015; Samaniego-Medina *et al.*, 2016; Drago *et al.*, 2017 and Augustin, 2018.

swaps, especially as a proxy of default risk since the spread of CDS is a relatively pure pricing of the underlying entity's default risk (Zhang *et al.*, 2009). Indeed, CDS quotes are commonly considered as indicators of market participants' perceptions of default risk regarding underlying entities. There are various proxies of default risk but an increasing number of papers considers CDS instruments because given their characteristics, they have several major advantages over the other proxies. First, considering bonds, CDS spreads are directly observable unlike bond spreads which have to be calculated using a benchmark risk-free yield curve (Ericsson *et al.*, 2006; Longstaff *et al.*, 2005). However, as evidenced by Houweling and Vorst (2005), the choice of the risk-free reference asset may be problematic. Second, compared to bond spreads, CDS spreads appear to react more accurately and rapidly to new information regarding the underlying reference entity (Blanco *et al.*, 2005). According to Zhang *et al.* (2009), this could be partly attributed to the fact that CDSs are unfunded and do not face short-sale restrictions. This may also be due to important non-default components in bond spreads that obscure the impact of changes in the underlying entity's credit quality (Ericsson *et al.*, 2006). Third, an important advantage of using CDS data compared to bond data is that the maturities of CDS contracts are strictly standardized and fixed over time, unlike bond contracts' maturities which are not uniform across firms and vary considerably over time (Han and Zhou, 2015). The existence of different standardized maturities is also the main advantage of CDS data compared to stock data. Credit default swaps offer a unique opportunity because of the ability to contemporaneously observe multiple instruments that measure the risk associated with the same bank, but at different horizons (Lok and Richardson, 2011). This cannot be obtained using stock prices which only indicate the current value (risk) of the bank. In light of these benefits, we consider CDS to be the most appropriate instrument available to apprehend the financial strength of banking institutions and appreciate the risk of default associated with the same institution, but at different maturities (horizons). However, which maturity(ies) should be considered to proxy for this bank default risk? Is there one or several maturities of CDS that might contain or summarize all the information available on the default risk of a bank?

In the last decade, several empirical papers have been interested in the factors explaining the pricing of credit default swaps, i.e. the factors determining the spreads of CDS. At first, some studies consider in their empirical analysis the structural model of default by Merton (1974), which has long been a standard for estimating the probability of default of listed banks. For instance, Ericsson *et al.* (2009) investigate the linear relationship between CDS spreads and three theoretical determinants of default risk, namely equity volatility, leverage, and risk-free interest rates. They find that these three variables are statistically and economically significant in explaining CDS spreads and spread changes. Moreover, they explain a large part of the variations in CDS spreads (approximately 60%) and a smaller part when considering CDS spread changes (approximately 23%). Numerous empirical papers subsequently confirm these findings, including Annaert *et al.* (2013), Hasan *et al.* (2014), Galil *et al.* (2014) and Drago *et al.* (2017), which in addition, evidence that these three variables alone cannot explain CDS spreads and spread changes. Indeed, they find that banks' liquidity, stock returns, asset quality, earnings, size and several market and business variables (such as term structure slope, market returns, market volatility) complement the Merton model and play an important role in explaining CDS spreads and spreads changes. A proof of this is the fact that these extended models have a somewhat better explanatory power as they produce a higher adjusted R2 than the model of Ericsson *et al.* (2009). Another stream of the literature, which is quite recent, employs credit default swaps to analyze changes in banks' financial health and risks following an event in order to examine the impact of this event (Morgan *et al.*, 2014; Sahin and Haan, 2016; Flannery *et al.*, 2017; Georgescu *et al.*, 2017; Ahnert *et al.*, 2018, and Sahin *et al.*, 2020).

All of the studies cited above systematically consider the (spreads of the) 5-year CDS maturity to carry out their empirical analysis, arguing that it is generally considered to be the most liquid segment of the market (Völz & Wedow, 2011). However, very little is known about the CDS maturity that should be considered to proxy for the default risk of a bank and this paper aims to add to the literature by investigating this issue. If around the financial crisis of 2007–2008 the difference between the maturities of CDS in terms of liquidity was important, this is no longer the case especially when considering the European CDS market. As we demonstrate below (section 1.2.2), these differences have considerably decreased over time until they disappear over the past decade. The most traded maturity remains the 5-year but its proportion (when considering all maturities traded) decreases over time in favor of maturities that are less than 5 years (Bank for International Settlements, 2021). This may explain the significant increase in the liquidity of short-term maturities (in particular the 6-month and the 1-year), thus allowing us to consider in our empirical investigations all the different CDS maturities.

According to Ball and Cuny (2020), the term structure of a bank CDS spreads is a function of two components of investors' uncertainty about the bank's asset value: (*1*) uncertainty from immediately available information that are imprecise (Duffie and Lando, 2001) and (*2*) uncertainty created by the anticipated arrival of unpredictable economic shocks that will affect the bank's asset value throughout the future (Black and Scholes 1973; Merton 1976; Leland 1994). Unlike the first component, the second one varies with the time horizon of investors and is not conditional on the available information because of the unpredictable nature of future economic shocks. These two components of uncertainty offer different implications for the assessed probability of default and, therefore, the magnitude of CDS spreads at different horizons. More precisely, the authors highlight that in the short run, since the amount of time that investors are exposed to possible economic shocks is small, the uncertainty about the bank situation is primarily driven by the first component (i.e. the imprecision of immediately available information) while the influence of the second component (i.e. uncertainty about the occurrence of shocks) is relatively negligible. As a consequence, the first component of uncertainty has a stronger influence on short-term CDS spreads while the influence of the second component is relatively weak or insignificant. And the more the CDS maturity increases, the more the relative influence of the second component increases since investors are increasingly exposed to unexpected possible economic shocks (Ball and Cuny, 2020). For example, a market participant who wants to trade a short-term maturity CDS contract (such as 6-month or 1-year contracts) will be more concerned about uncertainties about the situation of the reference entity (the imperfection of available information) than uncertainties about the ability of the latter to cope with macroeconomic shocks that may occur in the future. And the more the maturity of the contract will increase, the more his interest in the resilience of the reference entity to unexpected macroeconomic shocks will increase.

In view of the above, a change in the investors' uncertainty about a bank would not have the same impact on the latter's CDS spreads. This impact would differ depending on the maturity of the CDS contract and on whether it is a change in the first or the second component of uncertainty, or both. For instance, an official disclosure of new information about the bank situation (which corresponds to a shock to the first component of uncertainty) would affect all the different maturities of CDS. However, compared to the medium or long-term CDS spreads, the effect of this shock on short-term CDS spreads would be much stronger since the latter is predominantly driven by the first component. On the contrary, an official disclosure of new information about the ability of banks to absorb losses and to remain capitalized and solvent (which corresponds to a shock to the second component of uncertainty) would primarily affect medium and especially long-term CDS spreads (but little short-term CDS spreads) as the amount of time that market participants are exposed to possible economic shocks is high. Overall, spreads of each maturity would be impacted differently, suggesting that the spreads of the different maturities of CDS do not reflect the same aspect of the bank default risk.

To summarize, in presence of new information likely to affect market participants' uncertainty about a bank, and thus the probability of default of this bank, the spreads of the different CDS maturities do not vary the same. This therefore suggests that the premium of credit default swaps does not reflect the same information about the default risk of a bank, depending on the maturity of the CDS contract. As a result, one may wonder whether the 5-year maturity that is systematically chosen by the literature is the one that should be considered to proxy for the default risk of a bank. Or, is the sole consideration of the 5-year maturity sufficient? We therefore investigate if there is a CDS maturity that is representative of all others, i.e. if there is a maturity of CDS whose spread variations illustrate or summarize that of all the other maturities. For this purpose, we empirically examine how the spreads of the different CDS maturities behave, how they relate to each other, and how does a shock to one of the maturities influence the other maturities.

To carry out our empirical investigations, we employ a vector autoregressive (VAR) approach on a panel dataset of 49 European banks, over the 2010-2019 period, on a weekly basis. Extensively used in macroeconomics (Wu and Zhou, 2015) and now well-established in banking and finance, the VAR model is a multivariate time series model which allows us to relate current observations of a variable with past observations of itself and past observations of the other variables in the system. In this paper, the variables in the system are the spreads of the different maturities of CDS (6-month, 1-year, 2-year, 3-year, 4-year, 5-year, 7-year and 10-year maturities). We consider this model as it has the ability to capture the intertwined dynamics of multivariate time series data and, more importantly, it can overcome the endogeneity problem thus allowing all variables to be determined endogenously. The use of this model therefore makes it possible to avoid the potential bias resulting from the misspecification caused by the assumed exogeneity in simultaneous equation models (Sims, 1989). Also, VAR approach allows to identify the transmission of shocks between the system's variables since it allows to isolate the response of a given variable to fluctuations (shocks) in other variables in the system. As a consequence, VAR model appears to be the most appropriate to empirically examine the interaction between the spreads of the different maturities of CDS, and, to attempt to answer our research question.

Our findings indicate that the spreads of the different maturities of CDS are jointly determined since each of them is explained by both its previous realizations, and the previous realizations of other maturities' spreads. Using a Granger causality test (Granger, 1969), we evidence that each CDS maturity is *Granger-caused* by at least one of the remaining maturities. More precisely, there are strong causal linkages from the 6-month and the 2-year CDS maturities to all the remaining maturities. Going further, we provide strong evidence of the significant influence of the three shortest CDS maturities (the 6-month, 1-year and 2-year maturities) over all maturities. Indeed, the Forecast Error Variance Decomposition (FEVD) shows that whatever the maturity considered, a large part of its variation is explained by fluctuations in these three shortest CDS maturities, while fluctuations in the 3-year, 4-year, 5-year, 7-year and 10-year maturities only have a very limited impact. Our results therefore suggest that the

5-year CDS maturity may not be representative of all the others. By contrast, the dynamics in the three shortest CDS maturities might be useful to consider in order to get an overall representation of the dynamics of all the maturities. Furthermore, as the CDS spreads of these three short-term maturities are predominantly driven by the first component of uncertainty (the imprecision of immediately available information), their fluctuations are primarily explained by shocks to this component. This suggests that whatever the maturity of the CDS contract, the magnitude of its premium may be mainly influenced by the first component of uncertainty.

This paper contributes to the existing literature in the following ways. Firstly, we highlight that since the financial crisis of 2007–2008, the difference between the maturities of CDS in term of liquidity has decreased significantly over time until it disappears. To our best knowledge, this paper is the first to provide such empirical evidence thus questioning the "well-known" argument according to which the 5-year CDS maturity is the most liquid segment of the CDS market (among others, Corò *et al.*, 2013; Annaert *et al.*, 2013; Hasan *et al.*, 2014; Samaniego-Medina *et al.*, 2016; Drago *et al.*, 2017, Flannery *et al.*, 2017; Georgescu *et al.*, 2017; and Ahnert *et al.*, 2018). For instance, when considering our sample, the most liquid maturity in 2015, 2017, 2018 and 2019 is not the 5-year one, but rather the 1-year maturity (in 2015 and 2017) and the 6-month maturity (in 2018 and 2019). Secondly, we enrich the literature as our results demonstrate the existence of an interdependence between the spreads of the different maturities of CDS. We indeed show that whatever the maturity considered, the amount of information that the three shortest CDS maturities contributes to it is considerable and exceeds by far that of the remaining maturities. This suggests that a movement in each of the three shortest maturities provides an insight on the (future) dynamics of the other maturities. Hence, to examine the dynamics of CDS spreads (for example to analyze their change following an event), considering the spreads of the three shortest CDS maturities may be more relevant and more interesting compared to the spreads of the remaining maturities. To our best knowledge, this paper is the first to perform such empirical investigations and to provide such evidence. Thirdly, we add to the literature as our empirical results suggest that a shock to the two components of market participants' uncertainty will not have the same impact on the spreads of the different maturities of CDS. This is an important finding since it seriously questions the sole use by the literature of the 5-year maturity CDS spreads when examining the effect of a shock to these two components. For instance, we can cite regulatory banking stress tests whose outcomes are publicly disclosed at the end of each exercise, with the aim of impacting (reducing) the two components of market participants' uncertainty about tested banks (Morgan *et al.*, 2014; Sahin and Haan, 2016; Flannery *et al.*, 2017; Georgescu *et al.*, 2017; Ahnert *et al.*, 2018, and Sahin *et al.*, 2020). Our results suggest that to entirely measure the reaction of market participants and fully evaluate the informative content of this disclosure, using only the 5-year maturity spreads is not sufficient as it may lead to partial and incomplete results. The remaining CDS maturities (especially short-term maturities) matter and should also be considered.

The rest of the article is organized as follows. Section 1.2 describes the sample data considered in this study. Section 1.3 suggests and discusses our empirical strategy and specification tests. Section 1.4 presents the empirical results while Section 1.5 discusses the implications. Section 1.6 finally concludes the paper.

1.2. Data

1.2.1. Sample of Banks and CDS Contracts

To conduct our study, we consider a sample of banks for which information on tradable CDS contracts is available for all the different maturities, in the Bloomberg terminal. We first identify in this database, a total of 278 financial firms with tradable credit default swaps. We then restrict our main focus to banking institutions by selecting firms that belong to four industries of the financial sector (as defined in the Bloomberg terminal), namely "*Banks*", "*Diversified Banks*", "*Financial Services*" and "*Diversified Financial Services*". After this selection, we are left with 220 banking institutions ("banks" for short). We then remove banks whose headquarters are not in the US or Europe, resulting in 145 banks. Finally, we take out of the sample banks with no data available over the sample period 2010-2019. Consequently, our final sample consists of 60 banks with available information on tradable credit default swaps, including 49 European banks (from 14 countries) and 11 US banks. The sample's size is therefore precisely the same as Avino *et al.*'s (2019), and larger than samples used in previous studies. In Ballester *et al.* (2016), the sample is composed of 55 large banks (headquartered in the US and 14 EU countries) while Annaert *et al.*'s (2013) sample consists out of 32 listed European banks. Yang and Zhou (2013) and Eichengreen *et al.* (2012) have respectively a sample of 43 and 45 banks, headquartered in the US and in Europe.

To perform our empirical investigations, we consider the European sample (rather than the US sample) because of the limited number of US banking institutions with available information on tradable credit default swaps. For each of these European banks, we collect data on senior CDS spreads on a weekly basis, considering each of the eight CDS maturities. We get these data exclusively from the *CMA New York* source, which provides closing BID and ASK CDS quotes. Following the literature, we consider the MID spreads which is the average between the BID and the ASK spreads.

We conducted our study over the period from 2010 to 2019 because before 2010, the rate of missing data is too important. On average, over the period 2005-2007, 76% of the information on CDS spreads in our database is missing (80%, 78% and 71% of missing rate in 2005, 2006 and 2007 respectively, with almost no data available for the 6-month, 1-year, 2-year and 3-Year maturities). In 2008 and 2009, this rate is just as important even if it drops to 42% and 39%, respectively.

Overall, these choices help to ensure that our empirical investigations are based on actively traded instruments, in sufficient number. In the end, the study sample consists of a panel of 49 banks, with 10 years of data at the level of each bank (over the period 2010-2019 at a week frequency). The list of these banks (with their corresponding countries) is provided in Appendix 1.A.

1.2.2. Liquidity of CDS Contracts

In this sub-section, we analyze the liquidity of the different segments of the CDS market using the data available to us. To put it another way, we analyze the liquidity of the different maturities of CDS, over the 2010-2019 period. Liquidity in the CDS market reflects the ease with which traders can initiate a contract at an agreeable price (Tang and Yan, 2007). To measure it, following Tang and Yan (2013), Annaert *et al.* (2013) and Samaniego-Medina *et al.* (2016), we employ the absolute Bid-Ask spread (BAS) of the CDS quotes which is the most widely used CDS liquidity proxy in finance. It is the gap between ask and bid quotes, which narrows as the liquidity increases. Also, we employ this proxy because according to Tang and Yan (2010) and Bongaerts *et al.* (2011), it is significantly correlated to other major liquidity proxies such as number of quotes per CDS, data on trades or volume of orders, and others.

Appendix 1.B provides the summary statistics of absolute bid-ask spreads of all CDS maturities, and for each year over the 2010-2019 period. We also calculate a "BAS Ratio" statistic which is the average BAS of a maturity divided by that of the 5-Year maturity. This will allow us to compare the liquidity of the different maturities with each other. A BAS Ratio equal to 1 means that the maturity is as liquid as the 5-year maturity. When higher (lower) than one, this means that the maturity is less (more) liquid than the 5-year maturity.

According to our results, over the first four years (from 2010 to 2013), the most liquid maturities are that of 10-year, 7-year, 5-year and 4-year since their BAS Ratio is equal to or close to one. When considering the 3-year and 2-year maturities, the BAS Ratio is on average 1,3 and 1,5 respectively while it is 2,0 and 2,3 for the 1-year and 6-month maturities, which are therefore the least liquid maturities. Hence, from 2010 to 2013, higher maturities are the most liquidity. However, over the remaining period (from 2014 to 2019), the difference between maturities in terms of liquidity becomes increasingly insignificant. In general, the BAS Ratio is either equal to one or close to one whatever the maturity considered over these six years. Our results also indicate that the most liquid maturity in 2015, 2017, 2018 and 2019 is not the 5-year one, but rather the 1-year maturity (in 2015 and 2017) and the 6-month maturity (in 2018 and 2019).

Most of the papers that employ the CDS as instrument when performing their empirical investigations consider systematically the 5-year maturity contracts, arguing that it is by far the most liquid. However, our descriptive analysis shows that if the difference between the maturities of CDS in terms of liquidity was notable two decades ago, this is no longer the case because these differences have decreased over time until they disappear in recent years, at least when considering the European CDS market. This may be because even if the most traded maturity remains the 5-year, its proportion (when considering all maturities traded) decreases over time in favor of maturities that are less than 5 years[9].

1.3. Empirical Strategy and Specification Tests

1.3.1. Empirical Strategy

To empirically investigate the interaction between the spreads of the different maturities of CDS, and thus attempt to answer our research questions, we use a vector autoregressive (VAR) approach. Developed by Sims (1980) to model and analyze the inter-relations between several endogenously determined variables, VAR models have been extensively used in macroeconomics (Wu and Zhou, 2015) and are now well-established in banking and finance empirical literature (e.g., Blanchard, 1989; Bernanke and Blinder, 1992; Hoggarth *et al.*, 2005; De Graeve and Karas, 2010; Hammoudeh *et al.*, 2013; Mertens and Olea, 2018; Mumtaz and Theodoridis, 2020; Li et al, 2021).

Basically, the VAR model extends the idea of univariate autoregression to several time series regressions. It is a multivariate time series model that relates current observations of a variable with past observations of itself and past observations of the other variables in the system. In other words, a vector of time series variables is regressed on lagged vectors of these variables. This is one of the advantages of the VAR model over other methods since it has the ability to capture the intertwined dynamics of time series data and, more importantly, it can overcome the endogeneity problem thus allowing all variables to be determined endogenously. Also, according to Li *et al.* (2021), using an VAR approach avoids the potential bias resulting from the misspecification caused by the assumed exogeneity in simultaneous equation models

[9] More precisely, data from Bank for International Settlements (2021) shows that single-name contracts with maturities less than or equal to 1 year (essentially 1-year maturity contracts) represent 7,8% of the total notional amount insured in 2007. This proportion then increases to reach 12,5% in 2010 and 24,5% in 2019. By contrast, contracts with maturities beyond five years represent 32,1% of the total notional amount in 2007, before falling to 19,2% in 2010 and 8,4% in 2019. Finally, contracts with maturities over one year and up to five years represent 60,1% in 2007, 68,3% in 2010 and 67,1% in 2019.

(Sims, 1980) and it has the merit of avoiding a complete specification of the models (Bagliano and Favero, 1998).

This approach therefore seems to provide an appropriate method to examine the interaction and the dynamics between the spreads of the different maturities of CDS. Additionally, it will allow us to identify the transmission of shocks (using a recursive identification strategy) between the spreads of the different maturities, estimate the impact and isolate the response.

As our study is based on a panel dataset constructed for a sample of 49 banks over the period 2010-2019 at a week frequency, we specifically apply in this paper a panel-data vector autoregressive (panel VAR) framework developed by Love and Zicchino (2006). In the traditional VAR approach, there are some usual econometric limitations (for example, cross-sectional homogeneity is assumed). The advantage of the panel VAR approach lies in the fact that not only it uses the traditional VAR approach (with all the advantages associated with it), but also it uses the panel-data method thus accounting for unobserved individual heterogeneity, resulting in an improved consistency of the estimation (Love and Zicchino, 2006). Canova and Ciccarelli (2013) summarizes this by pointing out that all variables in the system are treated as endogenous and interdependent, both in a dynamic and in a static sense, although in some relevant cases, time-varying exogenous variables could be included.

In our empirical investigations, we only consider endogenous variables (the spreads of the different maturities). More precisely, in our panel VAR system, we model all spreads in the first (logarithmic[10]) difference following Hammoudeh *et al.* (2013), among others. This will allow us to study the Impulse Response Functions (IRFs) of different shocks and how these affect other imbalances. Table 1.1 summarizes the descriptive statistics for each CDS maturity. Our model has therefore the following form:

$$y_{i,t} = A_1 y_{i,t-1} + \ldots + A_p y_{i,t-p} + u_i + \varepsilon_{i,t} \tag{1}$$

[10] The spreads of CDS being highly skewed, we consider their logarithmic form to obtain a more "normal" distribution, and thus, to improve the model fit.

where:

$y_{i,t}$ is a (1,8) dimension vector of the eight maturities' spreads of bank i at time t. $y_{i,t-p}$ captures the previous realizations of the spreads of the eight maturities and p is the lag order of the panel VAR model. u_i is the vector of time-invariant bank fixed effects while $\varepsilon_{i,t}$ is the error term.

To estimates the model, we use the generalized method of moments (GMM) following Downing, Underwood, and Xing (2009), Ronen and Zhou (2013)[11]. Indeed, GMM estimators generates consistent estimates for autoregressive models while OLS estimators or the fixed effects method leads to biased and inconsistent estimates due to the endogeneity in lagged dependent variables and in the other regressors (Blundell and Bond, 1998; Antoniou *et al.*, 2008). Furthermore, following Abrigo and Love (2016) suggestions and, among others, Li *et al.* (2021), we use the forward orthogonal deviation transformation (Arellano and Bover, 1995) to remove bank-fixed effects instead of the first difference transformation. Indeed, analyzing the performances of the GMM estimator of dynamic panel data model, Hayakawa (2009) evidence that the estimator of the model transformed by the forward orthogonal deviation tends to work better than that transformed by the first difference.

1.3.2. Specification Tests

1.3.2.1. Panel Unit Root Test

Despite all its advantages, VAR models must only be applied to stationary time-series data (Wu and Zhou, 2015) because unit roots lead to the weak instruments problem (Blundell and Bond, 1998). Also, it is essential that all of variables in the model should be stationary to guarantee the consistency and the stability of the estimation. Consequently, we check the stationarity of our time-series (the different maturities' spreads in first logarithmic difference) by performing three panel unit root tests: the Im, Pesaran, and Shin (2003) test, and following Li *et al.* (2021), the Fisher-type Augmented Dickey–Fuller test (Maddala and Wu, 1999) and the Fisher-type Phillips-Perron (1988) test.

[11] Technical implementation of GMM PVAR is based on the Stata codes developed in Abrigo and Love (2016).

The results (reported in the last three columns of Table 1.1) show that all our series are strongly stationary since, whatever the test considered, the null hypothesis of non-stationarity is systematically rejected at 1% level of significance.

1.3.2.2. Optimal Lag-Order Selection

A crucial part of building a VAR model is deciding the lag order. In a panel VAR analysis, a vector of time series variables is regressed on the lagged vectors of the same variables. Hence, we need to determine the optimal lag order.

To answer this question and following the literature, we calculate various summary measures whose analysis will aid the selection process of the optimal model. We adopt the method of Andrews and Lu (2001) who proposed consistent moment and model selection criteria (MMSC) for GMM models, based on Hansen's (1982) J statistic of overidentifying restrictions. The lag order is selected based on the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC) and the Hannan–Quinn Information Criterion (HQIC); the optimal lag being the one with the smallest value for at least two of these statistics.

According to the results (presented in Table 1.2), the second-order panel VAR model is a better specification than the first-order or the third-order model. Indeed, results show that unlike the second-order or the third-order model, the first-order model rejects the Hansen-J over-identification restrictions at the 1% level, indicating misspecification; therefore, it should not be selected according to Abrigo and Love (2016). Then, considering the remaining lag order, our results suggest that the second-order panel VAR model is a better specification than the third-order model since it has the smallest statistics whatever the information criterion considered (BIC, AIC or HQIC).

Table 1.1: Descriptive statistics of the spreads of the different maturities of CDS.

This table presents the descriptive statistics of the eight maturities' spreads (in first logarithmic difference). The sample consists of a panel of 49 banks, with 10 years of data at the level of each bank (over the period 2010-2019 at a week frequency). N is the number of firm-week observations. Mean is the average while SD is the standard deviation. Min is the Minimum while Max is the Maximum. p5, p50 and p95 correspond respectively to the 5th, 50th (Median) and 95th percentiles.
The last three columns report the results of three unit-root tests, namely the Im, Pesaran, and Shin test (IPS), the Fisher-type Augmented Dickey–Fuller test (ADF) and the Fisher-type Phillips-Perron test (PP). The results suggest that we can reject the null hypothesis of non-stationarity at the 1% level.

									Winsorized				Unit-root test		
Maturity	**N**	**Mean**	**SD**	**Min**	**p5**	**p50**	**p95**	**Max**	**Mean**	**SD**	**Min**	**Max**	**IPS**	**ADF**	**PP**
6M Spread	21391	-0,0020	0,2264	-3,2783	-0,2373	-0,0013	0,2332	3,3190	-0,0020	0,1579	-0,6030	0,6081	***	***	***
1Y Spread	21391	-0,0016	0,2109	-3,2864	-0,2272	-0,0001	0,2211	3,3269	-0,0011	0,1487	-0,5465	0,5965	***	***	***
2Y Spread	21391	-0,0014	0,1765	-2,9618	-0,1912	-0,0002	0,1916	3,0123	-0,0008	0,1252	-0,4406	0,4981	***	***	***
3Y Spread	21391	-0,0012	0,1595	-2,7025	-0,1715	-0,0003	0,1763	2,7605	-0,0004	0,1136	-0,3949	0,4605	***	***	***
4Y Spread	21391	-0,0011	0,1431	-2,4910	-0,1526	-0,0005	0,1586	2,5483	-0,0004	0,1026	-0,3646	0,4265	***	***	***
5Y Spread	21391	-0,0010	0,1365	-2,3209	-0,1457	-0,0002	0,1522	2,3782	-0,0005	0,1002	-0,3830	0,4221	***	***	***
7Y Spread	21391	-0,0007	0,1288	-2,1817	-0,1424	-0,0004	0,1467	2,2313	-0,0003	0,0957	-0,3557	0,3804	***	***	***
10Y Spread	21391	-0,0005	0,1252	-2,0697	-0,1396	-0,0004	0,1456	2,1055	-0,0002	0,0931	-0,3432	0,3623	***	***	***

Source: Authors' calculation.

Table 1.2: Lag order selection statistics for panel VAR estimated (Model and Moment Selection Criteria)

This table presents the results of the Model and Moment Selection Criteria (MMSC) for our panel VAR model. It reports at the level of each lag order, the Hansen J-Statistic and the corresponding p-value. BIC, AIC and HQIC show the results under different selection criteria. *** indicates the best selection.

Lag-order	**Hansen's J-Statistic**	**p-value**	**BIC**	**AIC**	**HQIC**
1	539,592	0,0000003	-3281,808	-228,408	-1225,064
2	352,2975	0,1034341	-2832,203***	-287,703***	-1118,249***
3	263,0759	0,3671999	-2284,524	-248,924	-913,362
4	195,7885	0,4105815	-1714,912	-188,212	-686,540

Source: Authors' calculation.

1.3.2.3. Validity and Stability Tests

Following Enders (2015) and Li *et al.* (2021), to attest the validity of our panel VAR model, we conduct a Hansen J test of overidentifying restriction with the null hypothesis that the over-identifying restrictions are valid. According to our results, the Hansen J-statistic is 429.34, thus showing that we cannot reject this null hypothesis.

Following the estimation of our panel VAR model, we compute the orthogonalized Impulse Response Functions (oIRFs) and the Forecast Error Variance Decomposition (FEVD) to track the impact of each variable over time (the horizons of up to 8 weeks are reported). However, model stability being a pre-condition for a correct estimation and interpretation of these statistics (Abrigo and Love, 2016), we check the stability of our estimated model. As shown by Lütkepohl (2005) and Hamilton (1994), this stability condition is satisfied only when the maximum modulus is strictly less than one (Enders, 2015; Abrigo and Love, 2016).

In this study, as shown in Appendix 1.C, the maximum modulus is 0.66 thus confirming that our model is stable.

1.4. Empirical Results

This section presents our empirical findings. In Table 1.3, we present the results of the estimation of our panel VAR model (Equation 1). We report in eight different columns (Columns (1) to (8)), the estimates of the eight different equations of our panel VAR system. As we can see, each variable in the model is explained by at least one of the other variables in the model. In other words, each maturity's spreads are determined by the spreads of at least one of the remaining maturities. Some maturities significantly drive all the remaining maturities while others do not have any influence.

1.4.1. Granger Causality

As the lag order of our panel VAR model is $p=2$, to evaluate the joint explanatory power of the two lags of each variable, we use the Granger causality test following Li *et al.* (2021), among others.

First proposed by Granger (1969), Granger-causality statistics test whether one time series is useful and statistically significant in forecasting another. In this paper, we perform this test at the level of each equation of our panel VAR model, the null hypothesis being that the coefficients of all lags of one variable are jointly equal to zero, which indicates no Granger causality (Li *et al.*, 2021).

Table 1.3: Panel Vector autoregression estimation results.

This table presents the estimates of our panel VAR model (1):

$y_{i,t} = A_1 y_{i,t-1} + \ldots + A_p y_{i,t-p} + u_i + \varepsilon_{i,t}$

After performing a Moment and Model Selection Criteria (Andrews and Lu, 2001), we evidence that the optimal lag order to consider is the second-order (p=2). We therefore estimate a second-order panel VAR model. Columns (1) to (8) show the estimates of the 8 equations in the system. These estimates are obtained using the generalized method of moments (GMM) following Abrigo and Love (2016), the bank-fixed effects being removed using the forward orthogonal deviation transformation (Arellano and Bover, 1995).
Hansen J-statistic reports the overidentifying restriction test results (and show that the overidentifying restrictions are valid). Maximum modulus reports the model stability test results, with a value below one indicating stability.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Maturity	6M Spread	1Y Spread	2Y Spread	3Y Spread	4Y Spread	5Y Spread	7Y Spread	10Y Spread
6M Spread$_{t-1}$	1.370*	1.433**	1.668***	1.896***	1.925***	1.957***	1.805***	1.733***
	(0.762)	(0.725)	(0.586)	(0.557)	(0.517)	(0.520)	(0.452)	(0.428)
6M Spread$_{t-2}$	0.0874	-0.0279	-0.177	-0.211	-0.286	-0.329	-0.244	-0.241
	(0.308)	(0.297)	(0.257)	(0.252)	(0.246)	(0.252)	(0.210)	(0.202)
1Y Spread$_{t-1}$	0.0663	0.0291	-0.523	-0.894	-1.166*	-1.220*	-1.143*	-1.158**
	(1.058)	(1.007)	(0.809)	(0.761)	(0.699)	(0.701)	(0.607)	(0.578)
1Y Spread$_{t-2}$	-0.836*	-0.717*	-0.509	-0.357	-0.148	-0.0661	-0.103	-0.0269
	(0.440)	(0.431)	(0.361)	(0.348)	(0.324)	(0.328)	(0.279)	(0.269)
2Y Spread$_{t-1}$	-2.577**	-2.589**	-2.208**	-2.092**	-1.813**	-1.893**	-1.667**	-1.496**
	(1.138)	(1.104)	(0.896)	(0.846)	(0.769)	(0.764)	(0.662)	(0.635)
2Y Spread$_{t-2}$	1.681***	1.717***	1.569***	1.287***	1.052***	1.008**	0.893**	0.743**
	(0.588)	(0.594)	(0.491)	(0.465)	(0.407)	(0.401)	(0.352)	(0.340)
3Y Spread$_{t-1}$	-1.232	-1.203	-0.708	-0.620	-0.151	-0.0656	-0.0347	-0.0628
	(1.076)	(1.030)	(0.826)	(0.760)	(0.690)	(0.686)	(0.593)	(0.567)
3Y Spread$_{t-2}$	-0.324	-0.332	-0.384	-0.309	-0.475	-0.528*	-0.519**	-0.493**
	(0.442)	(0.437)	(0.355)	(0.335)	(0.299)	(0.297)	(0.258)	(0.248)
4Y Spread$_{t-1}$	3.512*	3.624**	2.744*	2.778**	1.974*	2.200*	2.021**	2.194**
	(1.912)	(1.823)	(1.446)	(1.338)	(1.180)	(1.159)	(1.005)	(0.950)
4Y Spread$_{t-2}$	-0.898	-1.025*	-0.698	-0.549	-0.123	-0.155	0.00187	0.00502
	(0.624)	(0.601)	(0.461)	(0.426)	(0.384)	(0.382)	(0.330)	(0.317)

5Y Spread$_{t-1}$	-1.968	-2.096	-1.638	-1.789*	-1.396*	-1.623**	-1.429**	-1.533**
	(1.387)	(1.311)	(1.027)	(0.941)	(0.837)	(0.827)	(0.717)	(0.678)
5Y Spread$_{t-2}$	0.394	0.553	0.345	0.307	0.154	0.280	0.0249	0.0308
	(0.474)	(0.455)	(0.346)	(0.318)	(0.285)	(0.284)	(0.247)	(0.238)
7Y Spread$_{t-1}$	-0.624	-0.795	-0.597	-0.350	-0.191	-0.0755	-0.00266	0.225
	(1.235)	(1.167)	(0.952)	(0.889)	(0.828)	(0.823)	(0.712)	(0.686)
7Y Spread$_{t-2}$	-0.231	-0.204	-0.0792	-0.0228	-0.151	-0.220	-0.196	-0.190
	(0.488)	(0.470)	(0.398)	(0.376)	(0.335)	(0.326)	(0.268)	(0.255)
10Y Spread$_{t-1}$	1.032	1.198	0.848	0.619	0.333	0.235	-0.0486	-0.409
	(0.902)	(0.863)	(0.705)	(0.662)	(0.614)	(0.611)	(0.531)	(0.513)
10Y Spread$_{t-2}$	0.115	0.0103	-0.0842	-0.155	-0.00717	0.0325	0.182	0.227
	(0.401)	(0.388)	(0.342)	(0.327)	(0.287)	(0.275)	(0.222)	(0.212)
Observations	21,391	21,391	21,391	21,391	21,391	21,391	21,391	21,391
Number of Banks	49	49	49	49	49	49	49	49
Number of Weeks	436.6	436.6	436.6	436.6	436.6	436.6	436.6	436.6

Source: Authors' calculation.

The results presented in Table 1.4 clearly show that the 6-month maturity's spreads *Granger-cause* at the 1% level, the spreads of all the remaining maturities except the 1-year. Likewise, the 2-year maturity's spreads also *Granger-cause* the spreads of all the remaining maturities at the 1% level (maturity of 1-year and 3-year) and at the 5% level (maturity of 6-month, 4-year, 5-year, 7-year and 10-year). To sum up, the spreads of all CDS maturities are *Granger-caused* by that of the 6-month and the 2-year maturities, except when we consider the 7-year and 10-year maturities which are in addition *Granger-caused* by the 4-year and 5-year maturities' spreads (at the 5% level). Moreover, Table 1.4 highlights that almost all of the statistics that are significant (thus indicating Granger causality) are above the diagonal while below, almost all of the statistics are unsignificant. This finding suggests that in most cases, the spreads of a maturity is only *Granger-caused* by that of shorter maturities.

As a result, our results first suggest that there are strong causal linkages from the 6-month and the 2-year CDS maturities to all the remaining maturities. Second, there are strong causal linkages to the 10-year (7-year) CDS maturity not only from the 6-month and the 2-year maturities, but also from the 4-year and the 5-year maturities (4-year maturity).

Table 1.4: Granger causality matrix.

This table presents the Granger causality matrix. Each cell shows whether the row spread of CDS *Granger-causes* the column spread. Each cell reports the Chi-square statistics. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Maturity	6M Spread	1Y Spread	2Y Spread	3Y Spread	4Y Spread	5Y Spread	7Y Spread	10Y Spread
6M Spread	-	4.452	8.220**	11.648***	13.875***	14.259***	15.975***	16.385***
1Y Spread	4.504	-	3.886	4.095	4.346	4.044	5.143*	5.126*
2Y Spread	8.875**	9.432***	-	9.303***	7.907**	7.935**	8.191**	6.655**
3Y Spread	3.928	3.955	3.906	-	4.137	4.738*	5.887*	5.855*
4Y Spread	3.561	4.387	3.820	4.313	-	4.555	6.507**	8.594**
5Y Spread	2.013	2.700	2.555	3.635	3.053	-	5.602*	7.113**
7Y Spread	0.556	0.744	0.471	0.167	0.292	0.496	-	0.595
10Y Spread	1.334	1.942	1.595	1.219	0.303	0.152	0.711	-

Source: Authors' calculation.

1.4.2. Forecast Error Variance Decomposition and Impulse Response Functions

In this sub-section, based on the estimates of our panel VAR model, we go further by calculating the Forecast Error Variance Decomposition (FEVD) and the orthogonalized Impulse Response Functions (oIRFs) in order to track and examine the influence of each maturity over time (over an 8-week horizon).

In addition to the Granger causality analysis, we first calculate the Forecast Error Variance Decomposition (FEVD) which aids in the interpretation of a panel VAR model once it has been fitted (Lütkepohl, 2005). This variance decomposition indicates the amount of information each maturity contributes to the other maturities in the autoregression, thus allowing us to better apprehend how the different maturities influence each other. Put differently, this decomposition determines how much of the forecast error variance (FEV) of each of the variables can be explained by shocks to the other variables (Pesaran & Shin, 1998).

The results of this analysis are summarized in Table 1.5[12]. We calculate the proportion of forecast errors variance in each maturity that is explained by shocks to the other maturities and by its own shocks, over several forecast horizon. We present the results by considering eight forecast horizons (from the 1st to the 8th week following the initial shock). To facilitate the assessment of the FEVD results, we made a graphical representation (Appendix 1.D) of the results reported in Table 1.5.

Table 1.5: Forecast Error Variance Decomposition.

Panels A to H of this table reports the Forecast Error Variance Decomposition (in percentage) at the horizons of up to 8 weeks, for each maturity's spreads. Panel A, B, C, D, E, F, G and H applies respectively to the 6-month, 1-year, 2-year, 3-year, 4-year, 5-year, 7-year and 10-year maturity spreads. We calculate the proportion of forecast errors in each maturity that can be explained by orthogonal shocks to the other maturities and by its own shocks at each forecast horizon. The value in each cell reports the percentage of forecast error variation in each maturity explained by shocks to the column variable.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: FEVD for 6-Month Spread								
Horizon	**6M Spread**	**1Y Spread**	**2Y Spread**	**3Y Spread**	**4Y Spread**	**5Y Spread**	**7Y Spread**	**10Y Spread**
1	100,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
2	74,72%	9,62%	9,73%	0,35%	3,19%	1,41%	0,35%	0,64%
3	64,00%	12,24%	12,43%	3,06%	4,63%	1,86%	0,68%	1,09%
4	60,10%	12,79%	12,52%	4,21%	5,24%	1,84%	1,16%	2,13%
5	58,77%	12,52%	12,30%	4,70%	5,49%	1,81%	1,50%	2,91%
6	58,16%	12,39%	12,13%	4,78%	5,55%	1,93%	1,72%	3,33%
7	57,75%	12,48%	12,04%	4,75%	5,55%	2,13%	1,80%	3,50%
8	57,47%	12,60%	12,01%	4,73%	5,54%	2,30%	1,82%	3,54%
Panel B: FEVD for 1-Year Spread								
Horizon	**6M Spread**	**1Y Spread**	**2Y Spread**	**3Y Spread**	**4Y Spread**	**5Y Spread**	**7Y Spread**	**10Y Spread**
1	96,76%	3,24%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
2	69,96%	12,90%	10,53%	0,35%	3,20%	1,75%	0,38%	0,92%
3	58,91%	15,68%	12,79%	3,42%	4,60%	2,23%	0,88%	1,50%
4	55,14%	15,91%	12,79%	4,61%	5,23%	2,16%	1,45%	2,70%
5	53,83%	15,50%	12,51%	5,13%	5,48%	2,13%	1,86%	3,56%
6	53,22%	15,33%	12,32%	5,19%	5,55%	2,27%	2,10%	4,02%
7	52,80%	15,40%	12,23%	5,15%	5,55%	2,49%	2,19%	4,19%
8	52,51%	15,53%	12,18%	5,13%	5,53%	2,68%	2,21%	4,23%
Panel C: FEVD for 2-Year Spread								
Horizon	**6M Spread**	**1Y Spread**	**2Y Spread**	**3Y Spread**	**4Y Spread**	**5Y Spread**	**7Y Spread**	**10Y Spread**
1	88,87%	3,86%	7,27%	0,00%	0,00%	0,00%	0,00%	0,00%

[12] In each panel, the value in each cell reports the percentage of forecast error variance explained by shocks to the column maturity.

2	62,09%	18,61%	14,51%	0,45%	1,99%	1,53%	0,21%	0,62%
3	50,84%	21,82%	16,59%	3,59%	3,20%	1,98%	0,63%	1,34%
4	47,43%	22,05%	16,29%	4,89%	3,69%	1,94%	1,18%	2,53%
5	46,31%	21,49%	15,90%	5,46%	3,92%	1,90%	1,61%	3,42%
6	45,83%	21,21%	15,65%	5,54%	3,98%	2,05%	1,86%	3,89%
7	45,49%	21,20%	15,53%	5,50%	3,99%	2,27%	1,95%	4,07%
8	45,25%	21,29%	15,47%	5,48%	3,98%	2,46%	1,97%	4,11%

Panel D: FEVD for 3-Year Spread

Horizon	6M Spread	1Y Spread	2Y Spread	3Y Spread	4Y Spread	5Y Spread	7Y Spread	10Y Spread
1	79,73%	3,32%	12,54%	4,41%	0,00%	0,00%	0,00%	0,00%
2	53,63%	22,72%	16,44%	3,15%	1,59%	1,91%	0,22%	0,35%
3	43,51%	25,97%	18,20%	5,11%	2,75%	2,51%	0,68%	1,27%
4	40,07%	26,19%	17,68%	6,45%	3,26%	2,49%	1,35%	2,52%
5	39,01%	25,46%	17,20%	7,03%	3,53%	2,41%	1,85%	3,51%
6	38,58%	25,04%	16,90%	7,13%	3,62%	2,52%	2,16%	4,06%
7	38,28%	24,96%	16,74%	7,08%	3,63%	2,74%	2,28%	4,29%
8	38,06%	25,02%	16,66%	7,03%	3,63%	2,94%	2,31%	4,35%

Panel E: FEVD for 4-Year Spread

Horizon	6M Spread	1Y Spread	2Y Spread	3Y Spread	4Y Spread	5Y Spread	7Y Spread	10Y Spread
1	71,92%	2,44%	16,60%	5,07%	3,97%	0,00%	0,00%	0,00%
2	48,98%	25,35%	17,55%	3,57%	2,85%	1,50%	0,07%	0,12%
3	39,89%	29,63%	19,18%	5,18%	2,90%	2,09%	0,40%	0,73%
4	36,72%	30,29%	18,61%	6,54%	3,08%	2,16%	0,91%	1,70%
5	35,84%	29,70%	18,17%	7,14%	3,20%	2,09%	1,33%	2,54%
6	35,53%	29,25%	17,90%	7,28%	3,25%	2,16%	1,61%	3,03%
7	35,33%	29,11%	17,76%	7,25%	3,25%	2,33%	1,73%	3,24%
8	35,17%	29,12%	17,69%	7,21%	3,25%	2,50%	1,76%	3,30%

Panel F: FEVD for 5-Year Spread

Horizon	6M Spread	1Y Spread	2Y Spread	3Y Spread	4Y Spread	5Y Spread	7Y Spread	10Y Spread
1	66,32%	2,31%	17,44%	6,43%	5,95%	1,54%	0,00%	0,00%
2	44,84%	26,36%	17,25%	4,54%	3,89%	2,97%	0,08%	0,06%
3	36,40%	30,65%	18,74%	5,95%	3,60%	3,59%	0,45%	0,62%
4	33,43%	31,28%	18,15%	7,35%	3,68%	3,61%	0,97%	1,54%
5	32,65%	30,66%	17,71%	7,94%	3,77%	3,48%	1,41%	2,37%
6	32,40%	30,20%	17,44%	8,09%	3,80%	3,52%	1,70%	2,86%
7	32,23%	30,05%	17,31%	8,05%	3,80%	3,67%	1,82%	3,07%
8	32,09%	30,06%	17,24%	8,01%	3,79%	3,83%	1,85%	3,13%

Panel G: FEVD for 7-Year Spread

Horizon	6M Spread	1Y Spread	2Y Spread	3Y Spread	4Y Spread	5Y Spread	7Y Spread	10Y Spread
1	63,15%	1,87%	17,84%	6,71%	4,22%	1,06%	5,13%	0,00%
2	43,17%	25,57%	18,12%	4,45%	2,70%	2,92%	3,06%	0,00%
3	35,52%	30,24%	19,61%	5,77%	2,50%	3,62%	2,56%	0,18%
4	32,82%	31,40%	19,07%	7,00%	2,53%	3,80%	2,64%	0,74%
5	32,19%	31,08%	18,70%	7,58%	2,58%	3,71%	2,85%	1,31%

6	32,03%	30,73%	18,49%	7,75%	2,60%	3,70%	3,03%	1,67%
7	31,93%	30,60%	18,39%	7,74%	2,60%	3,79%	3,11%	1,83%
8	31,84%	30,60%	18,34%	7,71%	2,60%	3,89%	3,13%	1,88%

Panel H: FEVD for 10-Year Spread

Horizon	6M Spread	1Y Spread	2Y Spread	3Y Spread	4Y Spread	5Y Spread	7Y Spread	10Y Spread
1	59,33%	1,56%	17,44%	6,78%	4,80%	1,06%	6,61%	2,41%
2	40,67%	25,05%	17,33%	4,32%	2,96%	3,87%	4,11%	1,68%
3	33,62%	30,14%	18,56%	5,29%	2,60%	4,99%	3,39%	1,41%
4	31,00%	31,64%	18,08%	6,43%	2,54%	5,38%	3,29%	1,65%
5	30,38%	31,50%	17,76%	7,03%	2,56%	5,31%	3,42%	2,04%
6	30,25%	31,21%	17,58%	7,24%	2,57%	5,26%	3,57%	2,32%
7	30,19%	31,08%	17,50%	7,26%	2,57%	5,29%	3,64%	2,46%
8	30,13%	31,06%	17,46%	7,24%	2,57%	5,36%	3,67%	2,51%

Source: Authors' calculation.

- *Panel A (6-month maturity)*

According to our results, the variance in the 6-month maturity is entirely explained (at 100%) by its own fluctuations during the first week. This rate of 100% then drops to 75% (second week) and 64% (third week), before stabilizing at around 59% from the fourth week. This means that in the initial period, none of the fluctuations in the other maturities explain the variation in the 6-month maturity. However, in the second week (third week), the contribution of the 1-year and 2-year maturities to this variation rises respectively to 9,6% and 9,7% (12,2% and 12,4%). These rates and those of the remaining maturities do not change substantially from the 4th week.

Almost all of the variation in the 6-month maturity is explained by its own fluctuations and by fluctuations in the 1-year and 2-year maturities. Shocks in the remaining five maturities (3-year, 4-year, 5-year, 7-year and 10-year maturities) therefore have either no influence or a very limited influence in the 6-month maturity's variance.

- *Panel B (1-year maturity)*

In the initial period, approximately 96,8% and 3,2% of the variation in the 1-year maturity is explained by fluctuations in respectively the 6-month and the 1-year maturities. Over the next two weeks, the 6-month maturity's rate decreases (dropping to 70% in the second week and 59% in the third week) and seems to converge at around 53,5% while that of the 1-year maturity increases, reaching 12,9% and 15,7%

respectively in the second and third week before stabilizing at around 15,5% from the fourth week.

Hence, shocks to the 6-month, 1-year and 2-year maturities explain a very large share of the variance in the 1-year maturity whatever the period (following the initial shock) considered. Our results in this panel also show a weak influence of the fluctuations in the remaining five maturities on the variance of the 1-year CDS maturity.

- *Panel C (2-year maturity)*

The contribution of the 6-month maturity to the variance in the 2-year maturity is 88,9% in the initial period. This proportion then falls fairly rapidly to 62% and 51% in the second and third week respectively. By contrast, the contribution of the 1-year maturity (2-year maturity) rises rapidly going from 3,9% (7,3%) in the first week to 18,6% and 21,8% (14,5% and 16,6%), respectively in the second and third week. The system becomes relatively stable from the fourth week since the proportion of the variation in the 2-year maturity that is explained by fluctuations in the different maturities no longer changes considerably. From the 6-month, 1-year and 2-year maturities, this proportion is respectively 46%, 21% and 16% on average while it is lower than 6% when considering each of the remaining maturities. This confirms once again the very limited influence of the 3-year, 4-year, 5-year, 7-year and 10-year maturities.

- *Panel D, E, F, G and H*

When considering variances in the 3-year, 4-year, 5-year, 7-year and 10-year maturities, fluctuations in the 6-month maturity explains them respectively at 79,7%, 71,9%, 66,3%, 63,2% and 59,3% in the first week. In the second period, these rates drop to 53,6%, 49%, 44,8%, 43,2% and 40,7% respectively before stabilizing from the fourth week. Likewise, shock to the 1-year maturity explains these variances respectively at 3.3%, 2.4%, 2.3%, 1,9%, and 1,6% in the first period. But during the second week, these proportions increase considerably reaching 22,7%, 25,4%, 26,4%, 25,6%, and 25,1%, respectively. Shock to the 2-year maturity also explains the variances in the 3-year, 4-year, 5-year, 7-year and 10-year maturities at 12,5%, 16,6%, 17,4%, 17,8% and 17,4% respectively, in the initial period. From the second period, these proportions do not variate substantially even if a slight decrease is noted over the weeks. Fluctuations in the 6-month, 1-year and 2-year maturities therefore explain the greater part of the variation in the 3-year, 4-year, 5-year, 7-year and 10-year CDS maturities, thus confirming our previous findings.

Overall, our results provide strong evidence of the significant influence of the three shortest CDS maturities (the 6-month, 1-year and 2-year maturities) on all maturities. In other words, the three shortest CDS maturities help to explain the other maturities and the amount of information that each of them contributes to the other maturities is considerable. Whatever the maturity considered, a large part of its variation is explained by fluctuations in these three shortest CDS maturities. According to our findings, this influence slightly decreases over the weeks until it stabilizes from the fourth week. On the other hand, our results also evidence the weak influence of the 3-year, 4-year, 5-year, 7-year and 10-year maturities. As shown by the FEVD analysis, a shock in these maturities only explain a very little part of the remaining maturities' variance.

The FEVD results are therefore largely consistent with the insights from the Granger causality analysis. Consequently, in the light of the above, we support that none of the CDS maturities is independent of the others since each CDS maturity's spreads are influenced by that of at least one of the remaining maturities. Secondly, there are strong influence and causal linkages from each of the three shortest CDS maturities (the 6-month, the 1-year and the 2-year maturities) to all the remaining maturities. This suggests that a movement in these three maturities provides an insight on the (future) dynamics of the other maturities. Hence, to examine the dynamics of the spreads of CDS[13], considering the spreads of one of the three shortest CDS maturities appear to be more relevant and more interesting, compared to the spreads of the remaining maturities. Indeed, the results suggest that the dynamics of these latter are strongly influenced by that of the spread of the three shortest maturities, while the opposite is not true.

Overall, our empirical results suggest that the 5-year CDS maturity may not be representative of all the others as its fluctuations do not illustrate (summarize) that of

[13] For example, to analyze the change in CDS spreads following an event such as the publication of stress test results.

all the other maturities. In fact, our empirical results do not allow us to support the existence of a maturity that is representative of all others. However, they demonstrate the existence of maturities whose dynamics might be useful to consider in order to get a general representation of the dynamics of all maturities.

To complement our analysis, we estimate the orthogonalized Impulse Response Functions (oIRFs) which allow us to visualize and examine how an orthogonal shock to one of the CDS maturities affects the others over time, at the horizons of up to 8 weeks. The results are presented in Appendix 1.E and illustrated in Appendix 1.F. They highlight (i) how a one-standard-deviation of positive shock to one of the CDS maturities affects the other maturities in the system and (ii) how long it takes these maturities to revert to their steady states (state of equilibrium). Following Li *et al.* (2021), we estimate a 95% confidence interval for each oIRFs (that correspond to the grey area) using 2000 Monte Carlo simulation draws[14]. It indicates a statistically significant response if zero falls outside the 95% confidence interval. Panel A, B, C, D, E, F, G and H correspond to the oIRFs following a shock in the 6-month, 1-year, 2-year, 3-year, 4-year, 5-year, 7-year and 10-year maturity spreads, respectively.

In the Panel D, E, F, G and H of Appendix 6, confidence intervals include the zero line. This suggests that in most cases, the 3-year, 4-year, 5-year, 7-year and 10-year maturity spreads do not influence the other maturities. A shock in each of these maturities is not followed by a significant response in the other maturities. This is consistent with our findings from the Granger causality analysis and the FEVD analysis. On the other hand, the results show that a positive orthogonal shock in the 1-year and 2-year maturity spreads (Panel B and C respectively) is followed by a positive and significant response in all the remaining maturities at t=2, after a decrease in t=1. The effect of these shocks then dissipates from t=4, thus allowing maturities to revert to their steady states. This also supports our previous findings according to which (i) shocks in the three shortest CDS maturities influence the remaining maturities; (ii) influence that slightly decreases over the weeks until it vanishes from the fourth week (the system becomes relatively stable from the fourth week).

[14] As a robustness check, we also use 500, 1000 and 4000 draws. This does not make a difference to our results.

However, these findings are not confirmed by evidence from the Panel A since it can be seen that a positive orthogonal shock in the 6-month maturity generates a negative response in all the remaining maturities at t=1, response that becomes statistically insignificant and vanishes from t=2.

1.5. Discussions and Implications

As explained above, the two components of the market participants' uncertainty about the situation of a bank influence differently the bank's CDS spreads. In the short run, the first component of uncertainty (namely, the imprecision of immediately available information) has a stronger influence on short-term CDS spreads while the influence of the second component (namely, the uncertainty about the occurrence of shocks) is relatively weak or insignificant since the amount of time that market participants are exposed to possible economic shocks is small. As CDS maturity increases, the relative influence of the second component also increases (Ball and Cuny, 2020).

As the short-term CDS spreads are predominantly driven by the first component of uncertainty, fluctuations in these short-term spreads are mainly explained by variations in this component. Our results therefore suggest that a shock to this first component, that causes major variations in the 6-month, 1-year and 2-year maturities (so the short-term CDS maturities) also causes variations in all the remaining maturities, with a lower intensity. On the other hand, a shock to the second component of uncertainty, that cause variations in the medium and long-term CDS maturities only causes little or no variations in the short-term CDS maturities. Our empirical results are therefore in line with Ball and Cuny (2020), according to which the two components of the market participants' uncertainty about the situation of a bank offer different implications for the latter's assessed probability of default, and, therefore, the magnitude of its CDS spreads at different horizons. However, our results provide new evidence as they suggest that whatever the horizon considered, the magnitude of CDS spreads is primarily influenced by the first component of uncertainty. Indeed, whatever the CDS maturity considered, its spread variation is primarily explained by shocks to the first component of uncertainty since a very large part of this variation is explained by fluctuations in the three shortest CDS maturities. Hence, even if the two components of uncertainty influence differently the CDS spreads depending on the maturity, it appears that the uncertainty created by the anticipated arrival of unpredictable economic shocks (that will affect the bank's asset value throughout the future) only has little influence compared to that of the other uncertainty. As we show, only the uncertainty about the imprecision of immediately available information (Duffie and Lando, 2001) seems to mainly influence the CDS spreads, whatever the maturities.

In view of our findings, a simultaneous shock to the two components of uncertainty will not have the same impact on the spreads of the different maturities of CDS. More precisely, all the spreads, whatever the maturities of CDS will be mainly impacted by the shock to the first component, especially short-term CDS spreads. By contrast, the latter will be little or not impacted by the shock to the second component, unlike the medium and the long-term CDS spreads. Overall, all the spreads will therefore be impacted differently by the two simultaneous shocks, depending on the CDS maturity. This is an important finding since it seriously questions the sole use by the literature of the 5-year maturity CDS spreads when examining the informative value of regulatory stress tests. Indeed, a regulatory stress testing exercise is a scenario-based supervision tool used by banking supervisors to ensure that participating banks have sufficient financial strength to absorb losses and to remain solvent and strongly capitalized, even in a distressed economic environment. At the end of a test, supervisory authorities disclose the results to market participants in a very detail way in an attempt to reduce the latter's uncertainty about the tested banks. More exactly, this disclosure (*i*) improves the quality and the quantity of the information available on the tested banks' situation (thus reducing the first component), and (*ii*) provides valuable information on the ability of these banks to cope with crisis situations, i.e. their ability to absorb losses and to remain strongly capitalized, even in a difficult economic environment (thus reducing the second component). The disclosure of stress test results therefore represents a (simultaneous) shock to the two components of the market participants' uncertainty about tested banks. As a consequence, and according to our results, CDS spreads of tested banks would be impacted differently depending on the maturity of the CDS contract. Hence, to entirely measure the reaction of market participants following the disclosure of stress test outcomes, and fully evaluate the informative content of this disclosure, using only the 5-year maturity spreads may not be sufficient as it may lead to partial and incomplete results. The remaining CDS maturities (especially short-term maturities) matter and should be also considered.

1.6. Conclusion

The recent literature has extensively used credit default swaps, especially as a proxy of default risk and systematically considers the (spreads of the) 5-year CDS maturity, arguing that it is generally considered to be the most liquid segment of the market. However, very little is known about the CDS maturity that should be considered to proxy for the default risk of a bank. This paper addresses this issue by investigating whether there is one or several maturities of CDS that might contain all the information available on the default risk of a bank.

To perform our empirical investigations, we employ a panel vector autoregressive (panel VAR) approach on a panel of 49 European banks, over the period from 2010 to 2019 at a week frequency. This method not only allows us to examine the interaction and the dynamics between the different maturities' spreads, but also it allows us to examine the transmission of shocks, estimate the impact and isolate the response.

The results show that the spreads of the different maturities help explain each other. Indeed, the spreads of each CDS maturity are *Granger-caused* by the spreads of at least one of the remaining maturities, usually the 6-month and the 2-year maturities. This result is then confirmed by the Forecast Error Variance Decomposition (and partly by the orthogonalized Impulse Response Functions) which highlights the strong influence of the three shortest CDS maturities (the 6-month, 1-year and 2-year maturities) as whatever the maturity considered, a large part of its variation is explained by fluctuations in these three maturities. Hence, the dynamics in the three shortest CDS maturities might be useful to consider in order to get an overall representation of the dynamics of all the maturities. Finally, our results suggest that a shock to the two components of the market participants' uncertainty about a bank financial health have not the same impact on CDS spreads, depending on the maturity of the CDS contract.

Appendix 1

Appendix 1.A: List of banks and Countries in our final sample.

Bank Country	Bank Name	Bank Industry
AUSTRIA	Erste Group Bank AG	Banks
	Raiffeisen Bank International	Banks
BELGIUM	KBC Group NV	Banks
BRITAIN	3i Group PLC	Diversified Finan Serv
	Barclays Bank PLC	Banks
	HSBC Bank PLC	Banks
	Lloyds Bank PLC	Banks
	Man Group PLC	Diversified Finan Serv
	Standard Chartered PLC	Banks
DENMARK	Danske Bank A/S	Banks
FRANCE	BNP Paribas SA	Banks
	Credit Agricole SA	Banks
	Natixis SA	Banks
	Societe Generale SA	Banks
GERMANY	Commerzbank AG	Banks
	Deutsche Bank AG	Banks
	IKB Deutsche Industriebank AG	Banks
GREECE	Alpha Bank AE	Banks
	Eurobank Ergasias SA	Banks
	National Bank of Greece SA	Banks
	Piraeus Bank SA	Banks
IRELAND	Allied Irish Banks PLC	Banks
	Bank of Ireland	Banks
	DEPFA Bank PLC	Banks
	Permanent TSB Group Holdings PLC	Banks
ITALY	Banca Italease SpA	Diversified Finan Serv
	Banca Monte dei Paschi di Siena SpA	Banks
	Banca Nazionale del Lavoro SpA	Banks
	Banca Popolare di Milano Scarl	Banks
	Banco BPM SpA	Banks
	Intesa Sanpaolo SpA	Banks
	Mediobanca Banca di Credito Finanziario SpA	Banks
	UniCredit SpA	Banks
	Unione di Banche Italiane SpA	Banks
NETHERLANDS	ABN AMRO Bank NV	Banks
	ING Bank NV	Banks
NORWAY	DNB Bank ASA	Banks
PORTUGAL	Banco BPI SA	Banks
	Banco Comercial Portugues SA	Banks
SPAIN	Banco Bilbao Vizcaya Argentaria SA	Banks
	Banco de Sabadell SA	Banks
	Banco Popular Espanol SA	Banks
	Banco Santander SA	Banks
	Bankia SA	Banks
	Bankinter SA	Banks
	CaixaBank SA	Banks
SWEDEN	Skandinaviska Enskilda Banken AB	Banks
	Svenska Handelsbanken AB	Banks
	Swedbank AB	Banks

Source: Authors' calculation.

Appendix 1.B: Summary statistics of the absolute Bid-Ask spreads (CDS liquidity proxy).

To measure the liquidity of the different maturities of CDS contract, following Tang and Yan (2013), Annaert *et al.* (2013) and Samaniego-Medina *et al.* (2016), we use the absolute Bid-Ask spread of the CDS quotes, i.e. the difference between ask and bid quotes. As liquidity increases, the size of the bid-ask spread narrows.
In this appendix, considering our sample, we provide the summary statistics of the absolute bid-ask spreads (BAS) at the level of each year (from 2010 to 2019). In each Panel, **N** is the number of observations. **Mean** (**SD**) is the average (standard deviation). **BAS_Ratio** corresponds to the Mean BAS of a maturity divided by that of the 5-Year maturity. This will allow us to compare the liquidity of the different maturities with each other. A BAS Ratio equal to 1 means that the maturity is as liquid as the 5-year maturity. When higher (lower) than one, this means that the maturity is less (more) liquid than the 5-year maturity.

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
	6-Month	1836	39,0	55,6	17,7	2,36
	1-Year	1836	33,8	48,1	15,3	2,05
2	2-Year	1836	26,8	35,1	13,5	1,62
0	3-Year	1836	21,8	27,2	11,8	1,32
1	4-Year	1836	18,4	21,5	10,8	1,12
0	5-Year	1836	16,5	18,9	10,0	1,00
	7-Year	1836	15,8	17,6	9,4	0,96
	10-Year	1836	15,3	18,0	9,9	0,93
	All	14688	23,4	34,3	11,6	

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
	6-Month	1820	89,3	150,5	34,3	2,17
	1-Year	1820	83,5	147,6	30,5	2,03
2	2-Year	1820	61,6	99,1	25,9	1,50
0	3-Year	1820	49,5	77,5	22,1	1,20
1	4-Year	1820	44,0	73,6	20,6	1,07
1	5-Year	1820	41,1	74,7	18,6	1,00
	7-Year	1820	40,6	80,6	17,5	0,99
	10-Year	1820	41,3	94,1	15,2	1,00
	All	14560	56,4	105,7	20,3	

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
	6-Month	1873	126,6	238,6	46,1	2,43
	1-Year	1873	104,3	180,7	42,5	2,00
2	2-Year	1873	75,6	116,0	35,0	1,45
0	3-Year	1873	64,9	105,9	29,2	1,24
1	4-Year	1873	57,4	94,9	23,2	1,10
2	5-Year	1873	52,2	93,2	20,0	1,00
	7-Year	1873	54,7	100,8	20,3	1,05
	10-Year	1873	57,0	110,7	22,2	1,09
	All	14984	74,1	141,2	29,3	

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
	6-Month	1948	63,9	113,9	25,1	2,06
	1-Year	1948	63,1	109,4	24,5	2,04
2	2-Year	1948	49,0	71,7	22,4	1,58
0	3-Year	1948	42,1	58,0	20,0	1,36
1	4-Year	1948	36,6	47,6	20,3	1,18
3	5-Year	1948	31,0	41,7	20,0	1,00
	7-Year	1948	30,6	35,6	19,6	0,99
	10-Year	1948	29,5	34,3	20,0	0,95
	All	15584	43,2	71,8	20,0	

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
	6-Month	2132	26,1	41,2	12,8	1,52
	1-Year	2132	25,9	36,9	12,4	1,51
2	2-Year	2132	23,9	25,8	14,0	1,39
0	3-Year	2132	22,1	22,0	15,0	1,28
1	4-Year	2132	19,8	18,6	12,8	1,15
4	5-Year	2132	17,2	18,1	10,0	1,00
	7-Year	2132	20,2	17,2	15,0	1,17
	10-Year	2132	19,9	16,2	15,0	1,16
	All	17056	21,9	26,2	13,3	

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
	6-Month	2335	86,4	400,9	16,0	0,91
	1-Year	2335	79,0	324,0	14,3	0,83
2	2-Year	2335	98,2	394,5	15,1	1,03
0	3-Year	2335	108,6	465,4	16,5	1,14
1	4-Year	2335	96,7	428,4	13,1	1,02
5	5-Year	2335	95,2	444,3	10,0	1,00
	7-Year	2335	142,6	886,1	15,0	1,50
	10-Year	2335	121,5	605,7	15,5	1,28
	All	18680	103,5	521,2	14,6	

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
	6-Month	2385	81,2	199,1	19,7	1,06
	1-Year	2385	79,9	200,1	16,9	1,04
2	2-Year	2385	96,7	301,1	15,9	1,26
0	3-Year	2385	89,8	259,0	14,5	1,17
1	4-Year	2385	81,5	238,9	14,2	1,06
6	5-Year	2385	76,7	226,9	13,3	1,00
	7-Year	2385	71,5	191,9	16,4	0,93
	10-Year	2385	81,9	258,8	18,0	1,07
	All	19080	82,4	237,2	16,0	

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
	6-Month	2338	58,3	140,8	10,4	0,90
	1-Year	2338	57,2	136,4	10,7	0,88
2	2-Year	2338	58,2	141,8	11,6	0,90
0	3-Year	2338	71,3	190,6	11,6	1,10
1	4-Year	2338	66,1	177,6	11,6	1,02
7	5-Year	2338	64,8	178,8	10,9	1,00
	7-Year	2338	72,9	207,0	13,4	1,13
	10-Year	2338	91,1	306,7	15,2	1,41
	All	18704	67,5	192,4	11,9	

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
	6-Month	2341	36,0	86,3	8,8	0,97
	1-Year	2341	36,8	88,3	8,4	0,99
2	2-Year	2341	38,1	94,2	9,1	1,03
0	3-Year	2341	42,0	108,5	10,0	1,14
1	4-Year	2341	38,7	102,8	8,6	1,05
8	5-Year	2341	37,0	101,1	7,8	1,00
	7-Year	2341	40,7	101,1	10,4	1,10
	10-Year	2341	42,5	103,2	11,0	1,15
	All	18728	39,0	98,5	9,9	

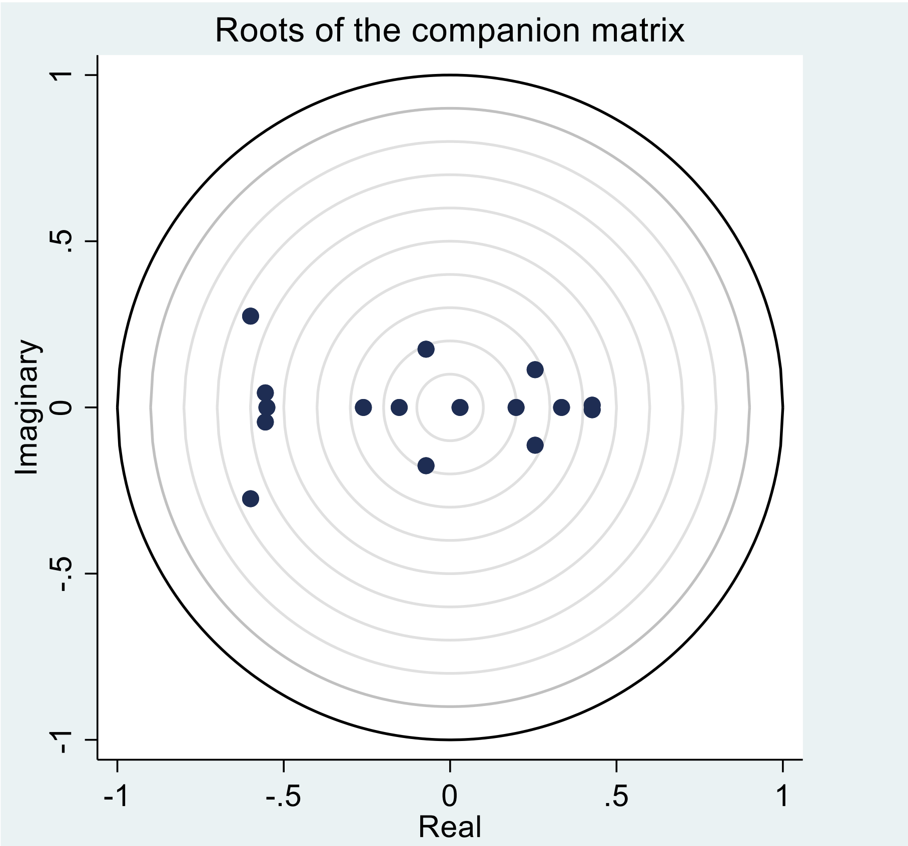
Year	Maturity	N	Mean	SD	Median	BAS_Ratio
	6-Month	2383	32,6	74,7	7,7	0,97
	1-Year	2383	33,9	79,3	8,3	1,01
2	2-Year	2383	34,7	83,4	9,1	1,03
0	3-Year	2383	33,4	80,4	8,9	0,99
1	4-Year	2383	32,7	77,5	8,8	0,97
9	5-Year	2383	33,6	79,6	8,1	1,00
	7-Year	2383	37,3	83,7	10,3	1,11
	10-Year	2383	41,1	92,5	12,1	1,22
	All	19064	34,9	81,6	9,8	

Source: Authors' calculation.

Appendix 1.C: Stability test (with Graph of eigenvalue stability condition).

Eigenvalue		Modulus
Real	**Imaginary**	
-0,5995875	-0,2746631	0,6595036
-0,5995875	0,2746631	0,6595036
-0,5553181	0,0438331	0,5570453
-0,5553181	-0,0438331	0,5570453
-0,5506506	0	0,5506506
0,4269604	0,0068978	0,4270161
0,4269604	-0,0068978	0,4270161
0,3348277	0	0,3348277
0,2555318	0,1136803	0,2796779
0,2555318	-0,1136803	0,2796779
-0,2606141	0	0,2606141
0,1983157	0	0,1983157
-0,0723643	0,175291	0,1896405
-0,0723643	-0,175291	0,1896405
-0,1530394	0	0,1530394
0,0297632	0	0,0297632

Source: Authors' calculation.

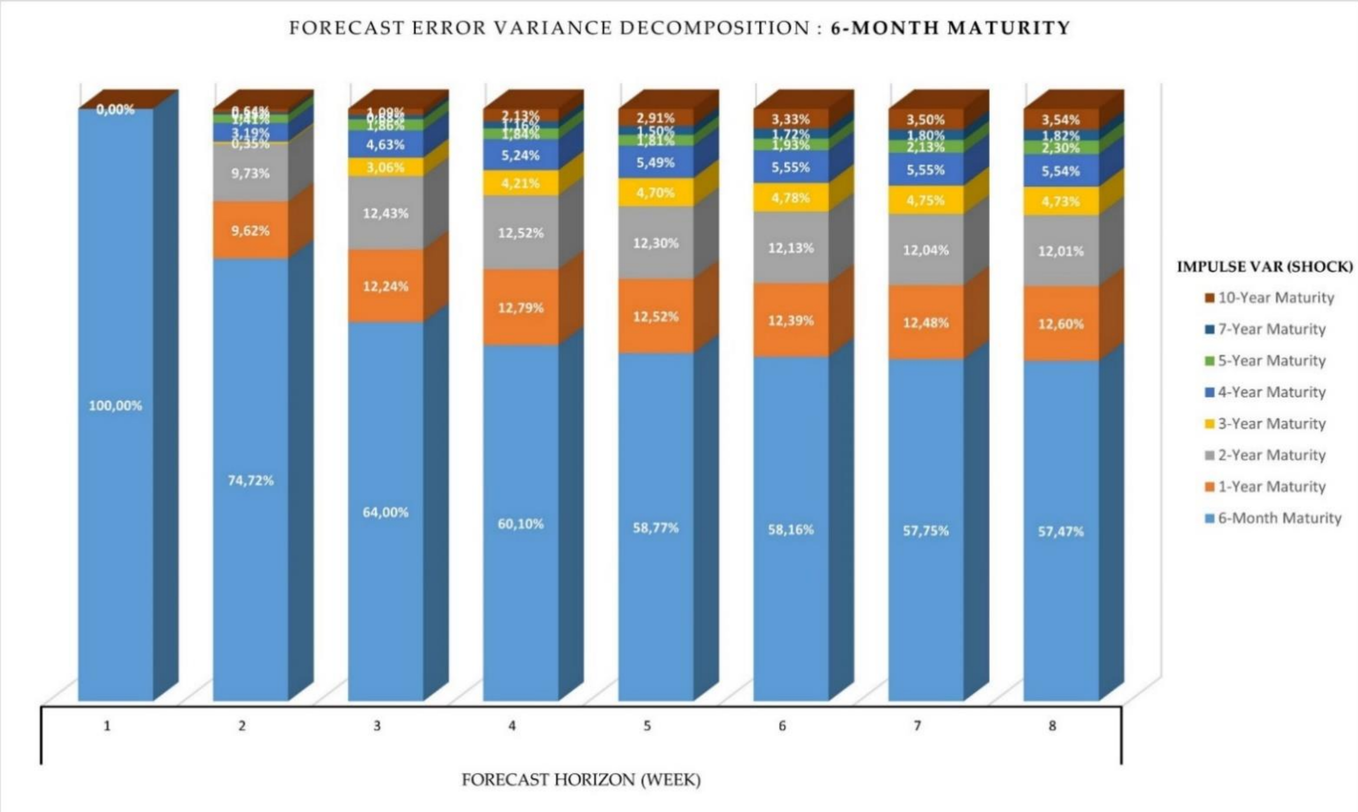


All the eigenvalues lie inside the unit circle. ***Panel VAR therefore satisfies stability condition***.

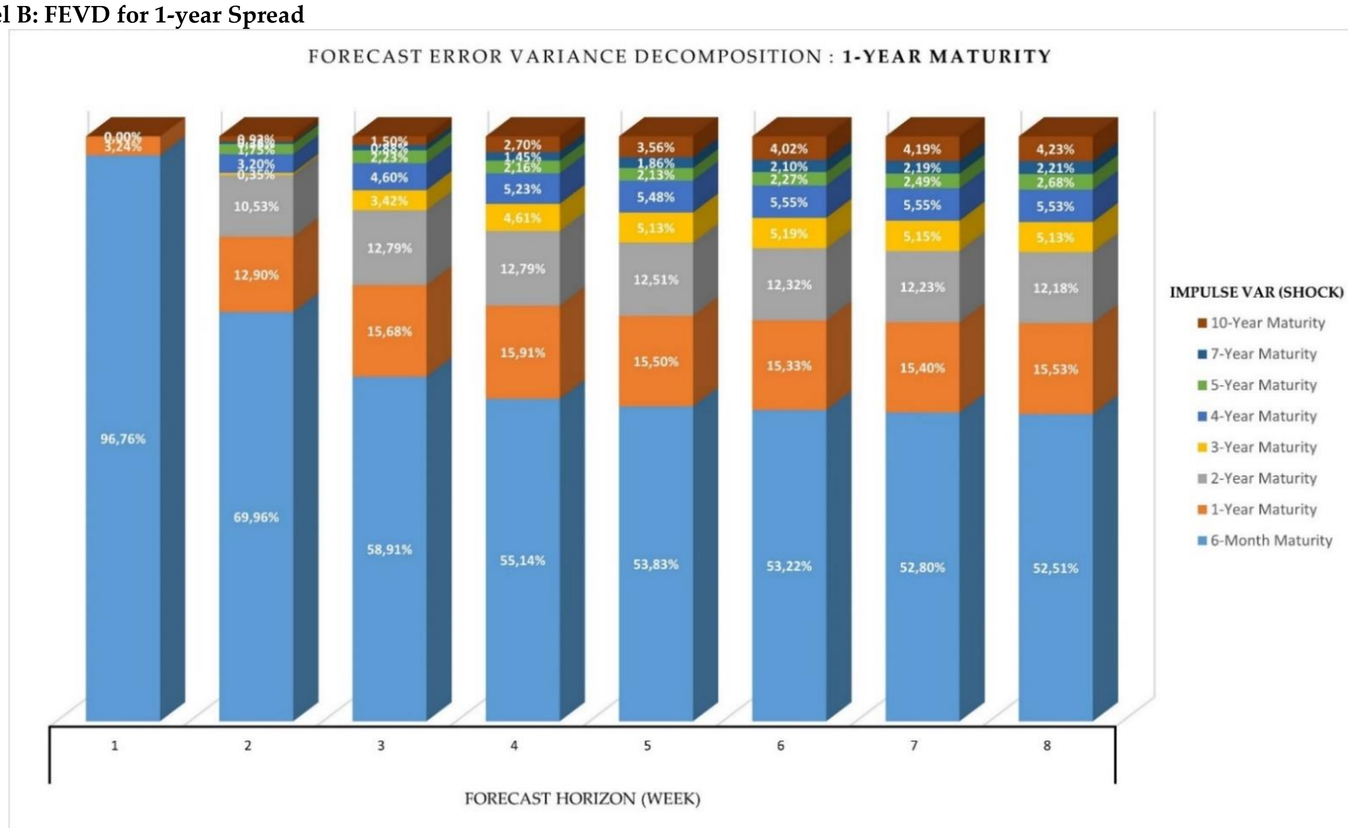
Appendix 1.D: Forecast Error Variance Decomposition.

Panels A to H of this appendix reports the Forecast Error Variance Decomposition (in percentage) at the horizons of up to 8 weeks, for each maturity. Panel A, B, C, D, E, F, G and H applies respectively to the 6-month, 1-year, 2-year, 3-year, 4-year, 5-year, 7-year and 10-year maturity. We calculate the proportion of forecast errors variance in each maturity that can be explained by orthogonal shocks to the other maturities and by its own shocks at each forecast horizon.

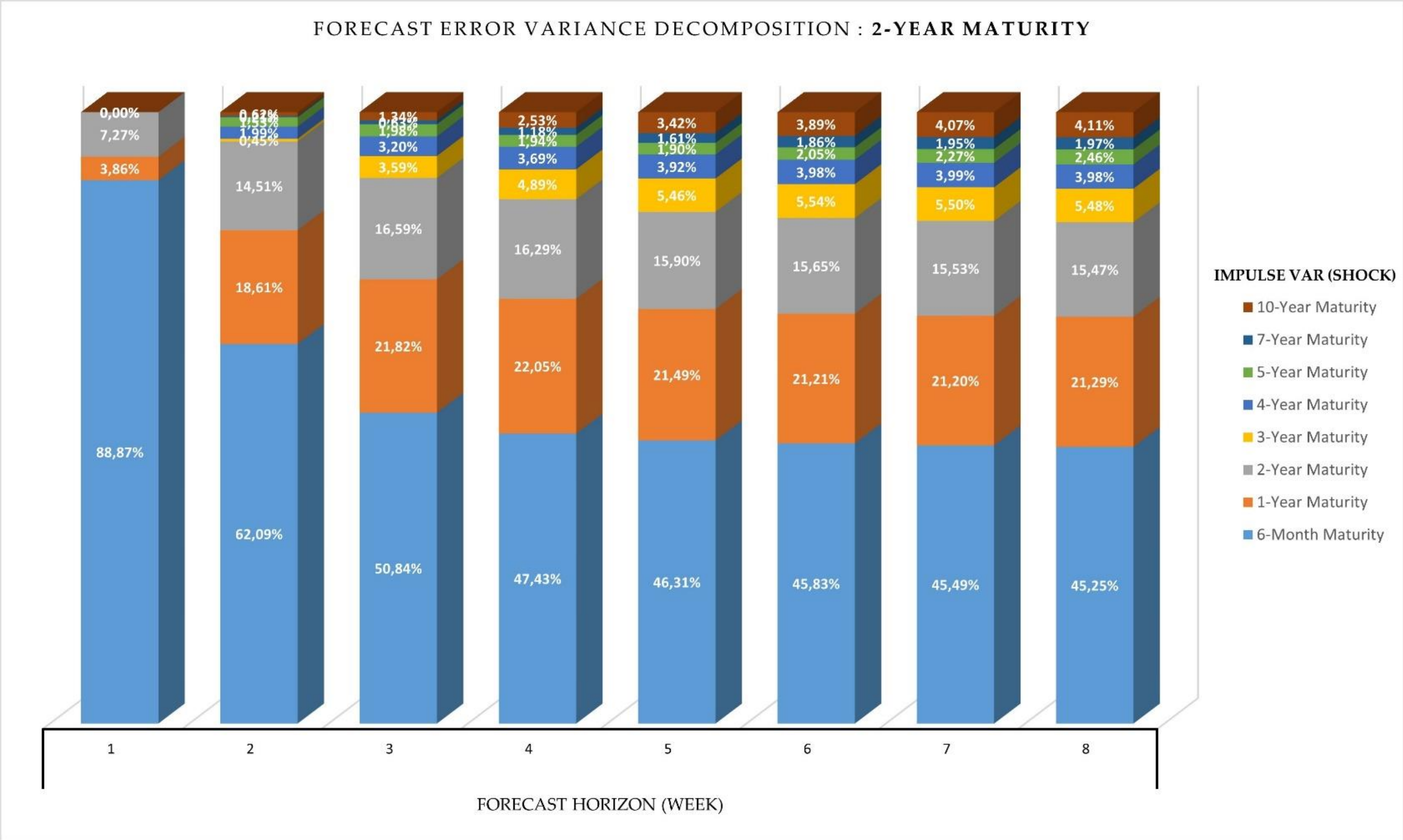
Panel A: FEVD for 6-Month Spread



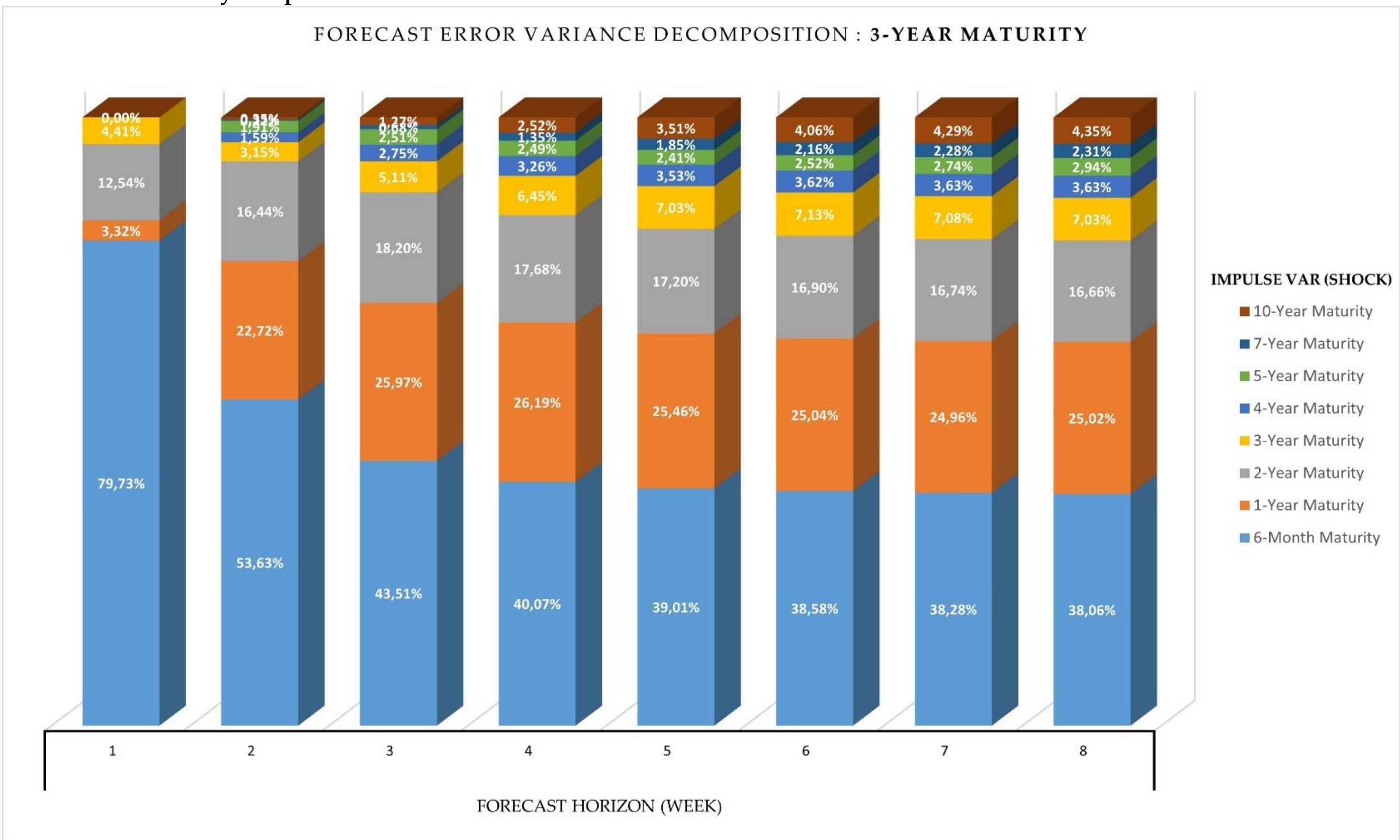
Panel B: FEVD for 1-year Spread



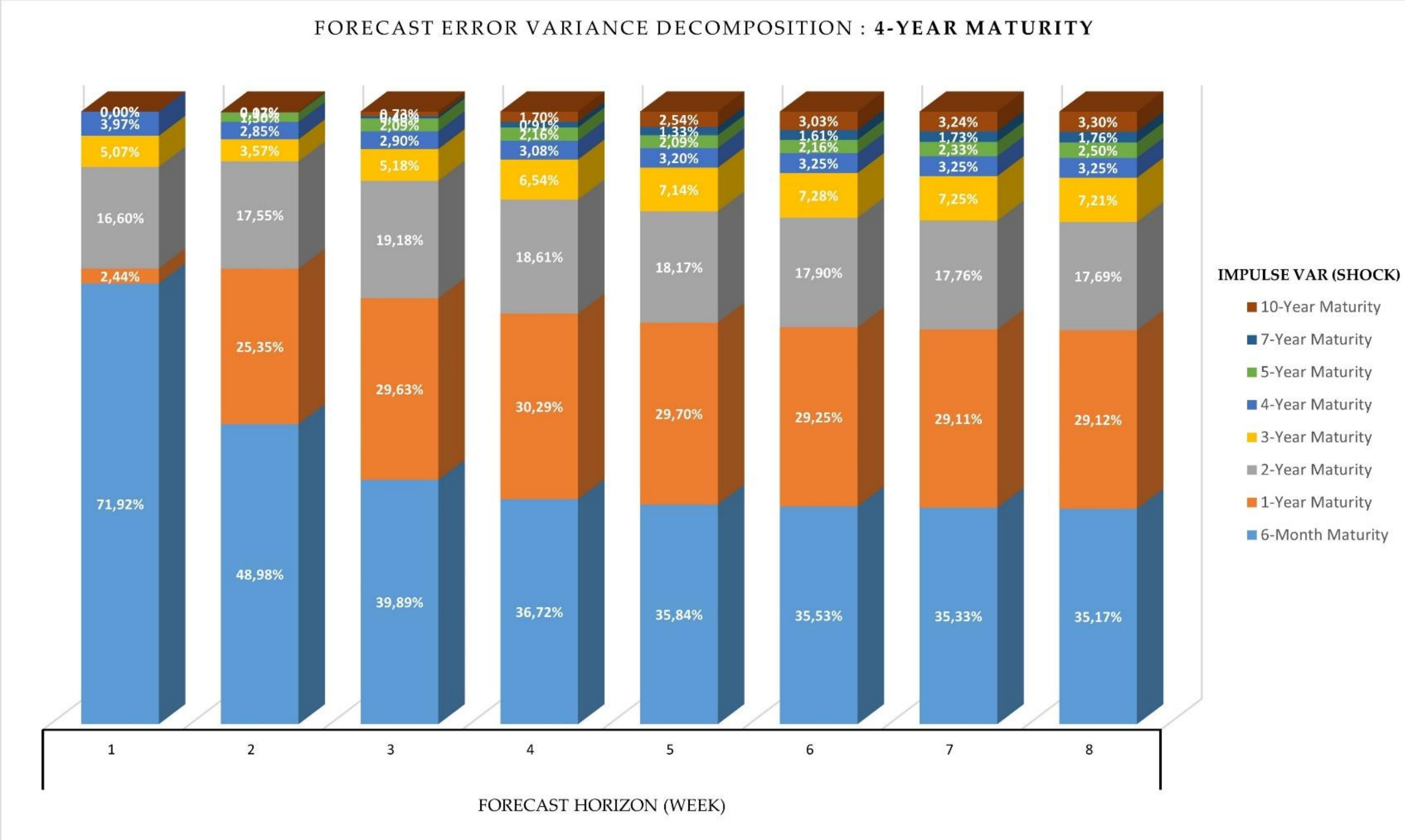
Panel C: FEVD for 2-year Spread



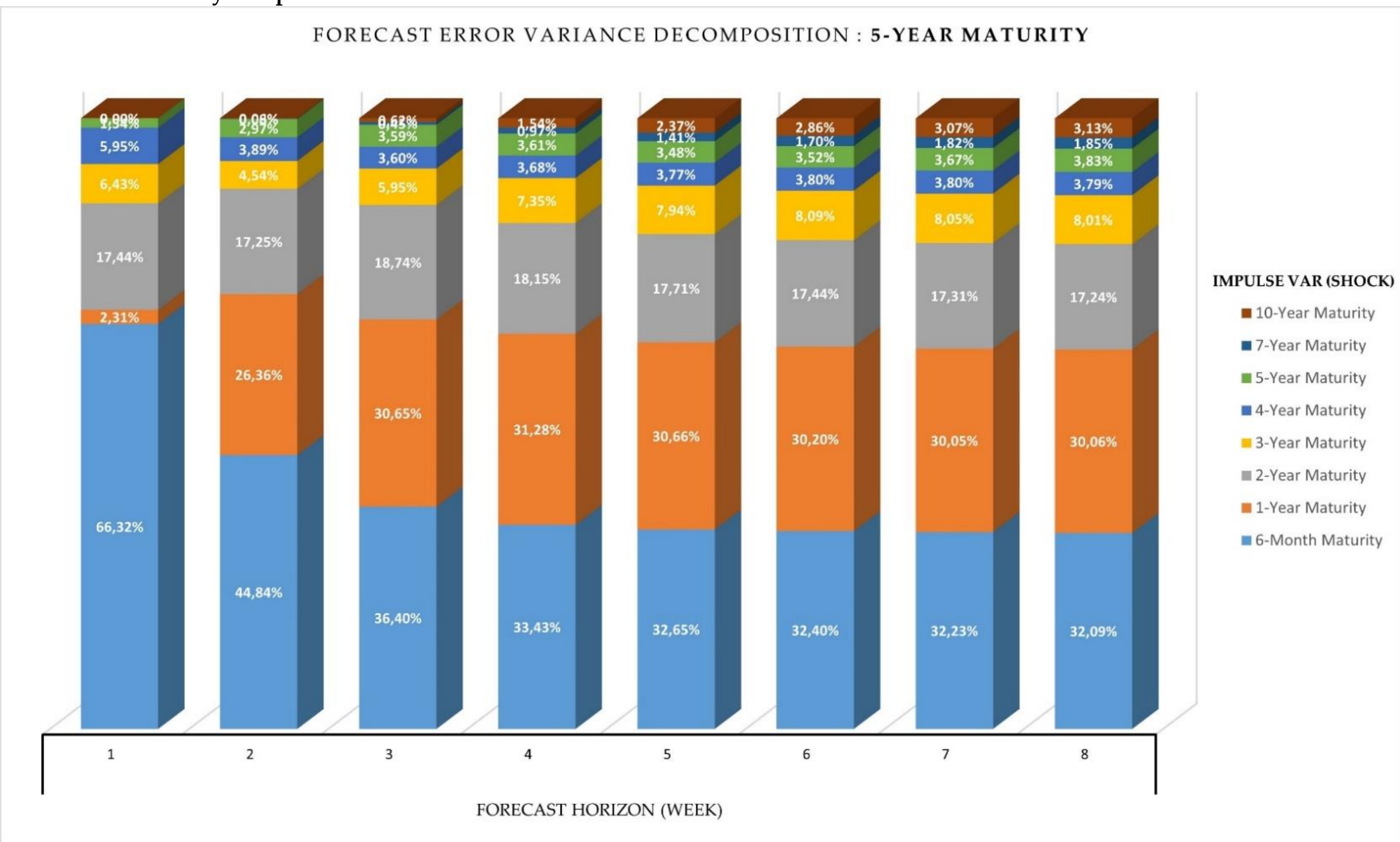
Panel D: FEVD for 3-year Spread



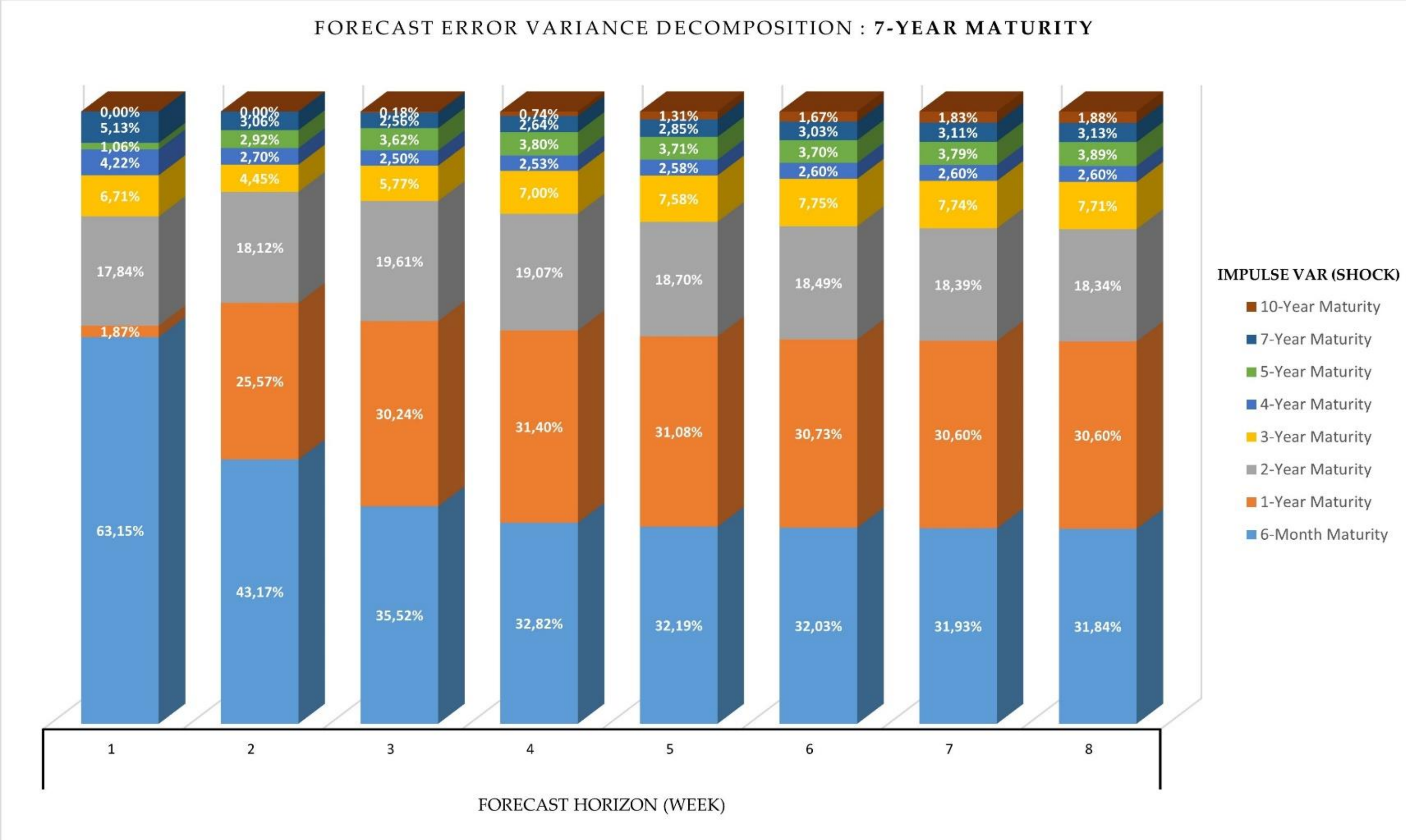
Panel E: FEVD for 4-year Spread



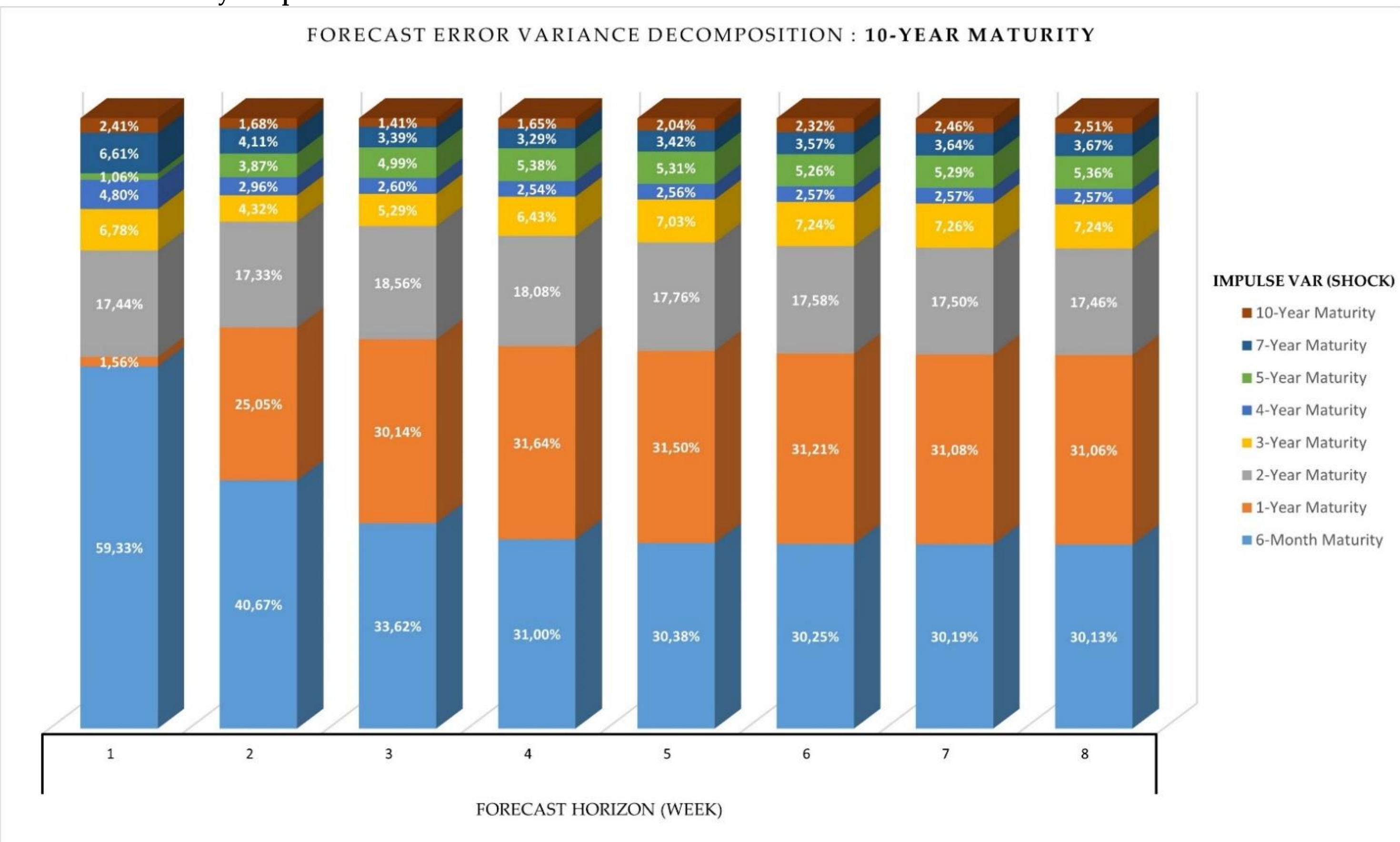
Panel F: FEVD for 5-year Spread



Panel G: FEVD for 7-year Spread



Panel H: FEVD for 10-year Spread



Source: Authors' calculation.

Appendix 1.E: Impulse-Response Functions (IRFs).

This table presents the results of the estimation of the orthogonalized Impulse Response Functions (oIRFs) which allow us to visualize and examine how an orthogonal shock to one of the CDS maturities affects the others over time. It highlights (i) how a one-standard-deviation of positive shock to one of the CDS maturities (first column) affects the other maturities and (ii) how long it takes these maturities to revert to their steady states (state of equilibrium). Following Li *et al.* (2021), we estimate a 95% confidence interval for each oIRFs using 2000 Monte Carlo simulation draws. It indicates a statistically significant response if zero falls outside the 95% confidence interval. IRF is the estimate of the response while LL (UL) is the Lower Limit (Upper Limit) of the 95% confidence interval.

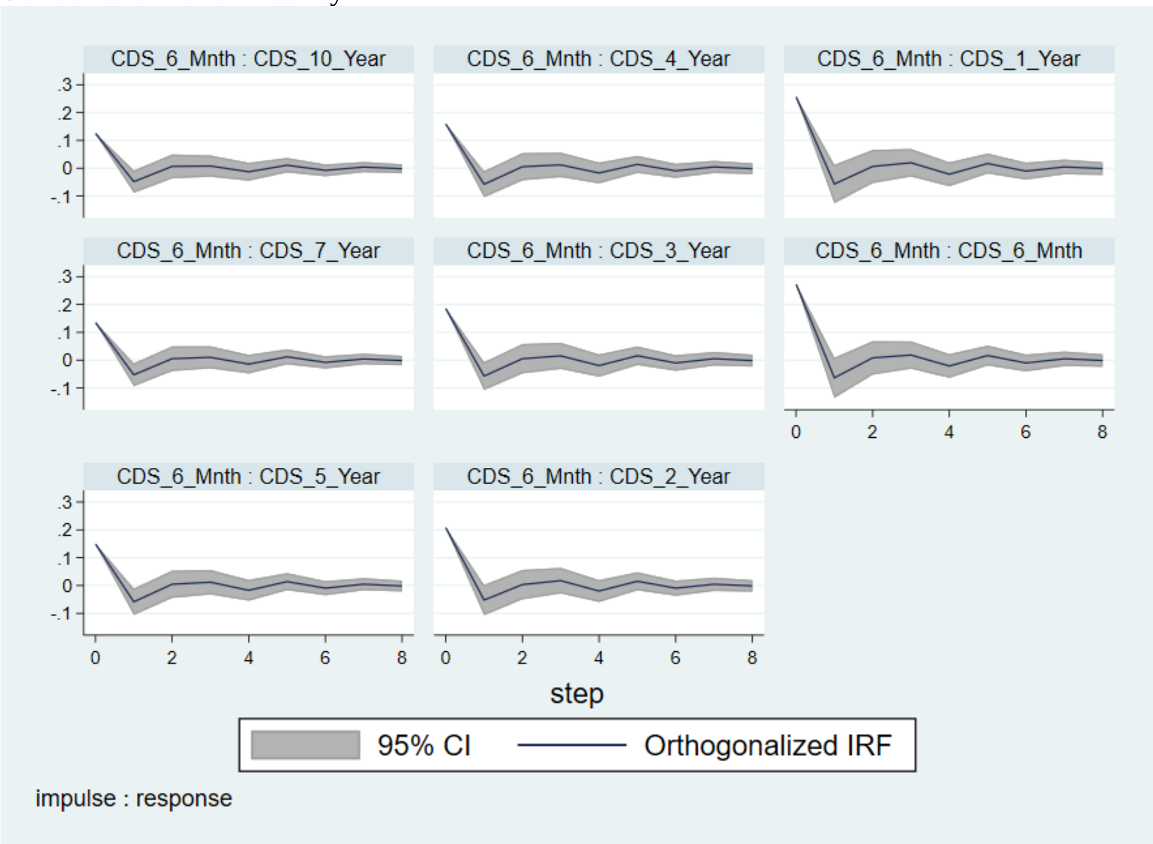
		Reponse Var																							
		6M Spread			1Y Spread			2Y Spread			3Y Spread			4Y Spread			5Y Spread			7Y Spread			10Y Spread		
Impulse Var	Horizon	IRF	LL	UL	IRF	LL	UL	IRF	LL	UL	IRF	LL	UL	IRF	LL	UL	IRF	LL	UL	IRF	LL	UL	IRF	LL	UL
Panel A Shock to 6M Spread	1	-6,4%	-13,6%	0,9%	-5,7%	-12,6%	1,2%	-5,2%	-10,7%	0,2%	-5,7%	-10,7%	-0,7%	-5,8%	-10,4%	-1,1%	-5,8%	-10,6%	-1,1%	-5,3%	-9,4%	-1,1%	-4,8%	-8,8%	-0,8%
	2	0,8%	-5,2%	6,8%	0,6%	-5,3%	6,6%	0,3%	-4,9%	5,6%	0,5%	-4,8%	5,8%	0,6%	-4,3%	5,5%	0,5%	-4,4%	5,4%	0,5%	-3,9%	5,0%	0,7%	-3,6%	5,0%
	3	1,8%	-3,1%	6,8%	2,0%	-3,0%	6,9%	1,8%	-2,8%	6,4%	1,5%	-3,2%	6,2%	1,2%	-3,2%	5,6%	1,2%	-3,2%	5,6%	1,0%	-3,0%	5,0%	0,8%	-3,0%	4,6%
	4	-2,1%	-6,4%	2,2%	-2,1%	-6,4%	2,1%	-2,0%	-5,9%	2,0%	-2,0%	-6,0%	2,1%	-1,7%	-5,4%	2,0%	-1,7%	-5,4%	2,0%	-1,4%	-4,8%	1,9%	-1,3%	-4,5%	2,0%
Panel B Shock to 1Y Spread	1	-10,1%	-17,4%	-2,8%	-10,3%	-17,2%	-3,3%	-10,9%	-16,5%	-5,3%	-12,0%	-17,4%	-6,7%	-11,8%	-16,8%	-6,8%	-12,0%	-17,0%	-7,0%	-10,9%	-15,3%	-6,6%	-10,3%	-14,5%	-6,2%
	2	7,0%	-0,5%	14,6%	7,5%	0,2%	14,9%	7,7%	1,1%	14,3%	8,1%	1,5%	14,7%	8,0%	1,8%	14,3%	8,1%	1,8%	14,4%	7,4%	1,8%	13,0%	7,1%	1,7%	12,5%
	3	-4,2%	-11,2%	2,8%	-4,1%	-11,1%	2,9%	-4,2%	-10,8%	2,4%	-4,8%	-11,5%	1,9%	-5,0%	-11,4%	1,4%	-5,0%	-11,5%	1,4%	-4,8%	-10,6%	1,0%	-4,8%	-10,4%	0,8%
	4	1,0%	-5,4%	7,5%	0,9%	-5,7%	7,6%	1,2%	-5,1%	7,5%	1,5%	-5,1%	8,0%	1,8%	-4,4%	8,1%	1,9%	-4,5%	8,2%	2,0%	-3,8%	7,7%	2,1%	-3,4%	7,7%
Panel C Shock to 2Y Spread	1	-10,1%	-16,7%	-3,5%	-10,2%	-16,5%	-3,9%	-8,5%	-13,5%	-3,4%	-7,8%	-12,6%	-3,0%	-6,6%	-11,0%	-2,2%	-6,3%	-10,8%	-1,9%	-6,1%	-9,9%	-2,2%	-5,5%	-9,3%	-1,8%
	2	7,1%	1,2%	13,1%	6,8%	0,9%	12,7%	6,5%	1,2%	11,8%	6,5%	1,2%	11,8%	5,9%	1,0%	10,9%	5,8%	0,9%	10,7%	5,3%	0,8%	9,8%	4,8%	0,4%	9,1%
	3	-3,4%	-8,6%	1,7%	-3,4%	-8,6%	1,8%	-3,0%	-7,9%	1,9%	-3,1%	-8,1%	1,9%	-2,9%	-7,6%	1,9%	-2,8%	-7,6%	2,0%	-2,6%	-6,9%	1,8%	-2,4%	-6,6%	1,8%
	4	1,3%	-3,1%	5,7%	1,2%	-3,3%	5,6%	1,1%	-3,1%	5,4%	1,3%	-3,2%	5,7%	1,2%	-3,0%	5,5%	1,2%	-3,1%	5,5%	1,1%	-2,8%	5,0%	1,1%	-2,7%	4,9%
Panel D Shock to 3Y Spread	1	1,9%	-4,1%	7,9%	1,9%	-3,9%	7,6%	1,8%	-2,9%	6,5%	1,8%	-2,7%	6,3%	1,7%	-2,4%	5,9%	2,1%	-2,1%	6,3%	1,5%	-2,1%	5,1%	1,1%	-2,3%	4,5%
	2	-5,8%	-11,3%	-0,4%	-6,1%	-11,5%	-0,6%	-5,4%	-10,3%	-0,5%	-4,7%	-9,7%	0,3%	-4,0%	-8,7%	0,6%	-4,0%	-8,7%	0,6%	-3,5%	-7,7%	0,6%	-3,0%	-7,1%	1,0%
	3	4,2%	-0,5%	8,9%	4,3%	-0,5%	9,0%	3,9%	-0,5%	8,3%	4,1%	-0,4%	8,6%	3,7%	-0,5%	8,0%	3,9%	-0,4%	8,1%	3,3%	-0,6%	7,2%	3,0%	-0,7%	6,7%
	4	-2,9%	-7,1%	1,3%	-2,9%	-7,1%	1,3%	-2,7%	-6,6%	1,1%	-2,8%	-6,8%	1,1%	-2,6%	-6,3%	1,1%	-2,6%	-6,3%	1,1%	-2,3%	-5,6%	1,1%	-2,2%	-5,4%	1,0%

Panel E Shock to 4Y Spread	1	5,8%	-0,7%	12,3%	5,6%	-0,5%	11,8%	3,8%	-1,0%	8,7%	3,3%	-1,0%	7,7%	1,6%	-2,2%	5,5%	1,5%	-2,3%	5,3%	1,0%	-2,3%	4,2%	0,7%	-2,5%	3,8%
	2	-4,8%	-11,1%	1,4%	-4,7%	-10,9%	1,4%	-3,8%	-9,2%	1,7%	-3,6%	-9,0%	1,9%	-2,0%	-7,1%	3,0%	-1,8%	-6,8%	3,2%	-1,3%	-5,8%	3,2%	-0,9%	-5,2%	3,4%
	3	3,5%	-2,5%	9,5%	3,5%	-2,5%	9,5%	2,7%	-2,9%	8,2%	2,7%	-3,0%	8,3%	1,8%	-3,4%	7,0%	1,8%	-3,5%	7,0%	1,2%	-3,5%	5,9%	1,0%	-3,5%	5,4%
	4	-2,3%	-7,7%	3,1%	-2,3%	-7,8%	3,2%	-1,9%	-7,0%	3,3%	-1,9%	-7,3%	3,4%	-1,4%	-6,3%	3,6%	-1,3%	-6,3%	3,7%	-0,9%	-5,4%	3,6%	-0,7%	-5,1%	3,6%
Panel F Shock to 5Y Spread	1	-3,9%	-9,6%	1,9%	-4,2%	-9,6%	1,3%	-3,4%	-7,7%	1,0%	-3,7%	-7,6%	0,3%	-3,0%	-6,5%	0,6%	-3,4%	-6,9%	0,0%	-3,3%	-6,4%	-0,3%	-3,8%	-6,6%	-1,0%
	2	2,9%	-2,5%	8,2%	3,0%	-2,3%	8,2%	2,6%	-2,1%	7,3%	2,9%	-1,8%	7,6%	2,5%	-1,8%	6,8%	2,9%	-1,4%	7,2%	2,7%	-1,1%	6,5%	3,1%	-0,5%	6,7%
	3	-1,1%	-6,0%	3,7%	-1,1%	-5,9%	3,8%	-1,0%	-5,5%	3,6%	-1,3%	-6,0%	3,3%	-1,4%	-5,7%	2,9%	-1,6%	-5,9%	2,7%	-1,8%	-5,6%	2,1%	-2,2%	-5,8%	1,5%
	4	-0,5%	-4,8%	3,8%	-0,6%	-4,9%	3,7%	-0,5%	-4,6%	3,6%	-0,3%	-4,5%	3,9%	-0,1%	-4,0%	3,9%	0,1%	-3,9%	4,0%	0,4%	-3,2%	3,9%	0,7%	-2,7%	4,1%
Panel G Shock to 7Y Spread	1	1,9%	-2,7%	6,5%	1,9%	-2,4%	6,3%	1,2%	-2,3%	4,8%	1,2%	-2,0%	4,5%	0,7%	-2,3%	3,6%	0,7%	-2,3%	3,7%	-0,2%	-2,8%	2,4%	-0,8%	-3,3%	1,6%
	2	-2,2%	-6,4%	2,0%	-2,6%	-6,7%	1,6%	-2,0%	-5,7%	1,7%	-2,1%	-5,8%	1,7%	-1,6%	-5,0%	1,9%	-1,6%	-5,1%	1,8%	-0,5%	-3,6%	2,6%	0,0%	-2,9%	2,9%
	3	2,6%	-1,6%	6,8%	2,8%	-1,4%	7,0%	2,4%	-1,4%	6,3%	2,6%	-1,3%	6,5%	2,1%	-1,6%	5,7%	2,1%	-1,6%	5,7%	1,4%	-1,9%	4,6%	1,0%	-2,0%	4,1%
	4	-2,3%	-6,2%	1,7%	-2,5%	-6,5%	1,5%	-2,2%	-5,9%	1,5%	-2,3%	-6,1%	1,5%	-1,9%	-5,5%	1,6%	-2,0%	-5,5%	1,6%	-1,4%	-4,5%	1,8%	-1,1%	-4,2%	1,9%
Panel H Shock to 10Y Spread	1	2,6%	-1,9%	7,1%	3,0%	-1,3%	7,3%	2,1%	-1,4%	5,7%	1,6%	-1,7%	4,8%	0,8%	-2,2%	3,9%	0,6%	-2,4%	3,6%	-0,1%	-2,7%	2,5%	-1,0%	-3,6%	1,5%
	2	-2,6%	-6,7%	1,5%	-2,9%	-6,9%	1,1%	-2,7%	-6,3%	0,8%	-2,9%	-6,5%	0,6%	-2,1%	-5,4%	1,1%	-2,0%	-5,2%	1,2%	-1,0%	-3,9%	1,8%	-0,4%	-3,1%	2,3%
	3	3,8%	-0,2%	7,9%	4,1%	0,0%	8,1%	3,5%	-0,1%	7,2%	3,6%	-0,1%	7,2%	2,8%	-0,5%	6,1%	2,7%	-0,5%	6,0%	1,9%	-1,0%	4,8%	1,4%	-1,3%	4,2%
	4	-3,4%	-7,3%	0,6%	-3,5%	-7,4%	0,4%	-3,1%	-6,7%	0,4%	-3,3%	-6,9%	0,4%	-2,7%	-6,0%	0,6%	-2,7%	-6,0%	0,7%	-2,0%	-4,9%	0,9%	-1,6%	-4,4%	1,2%

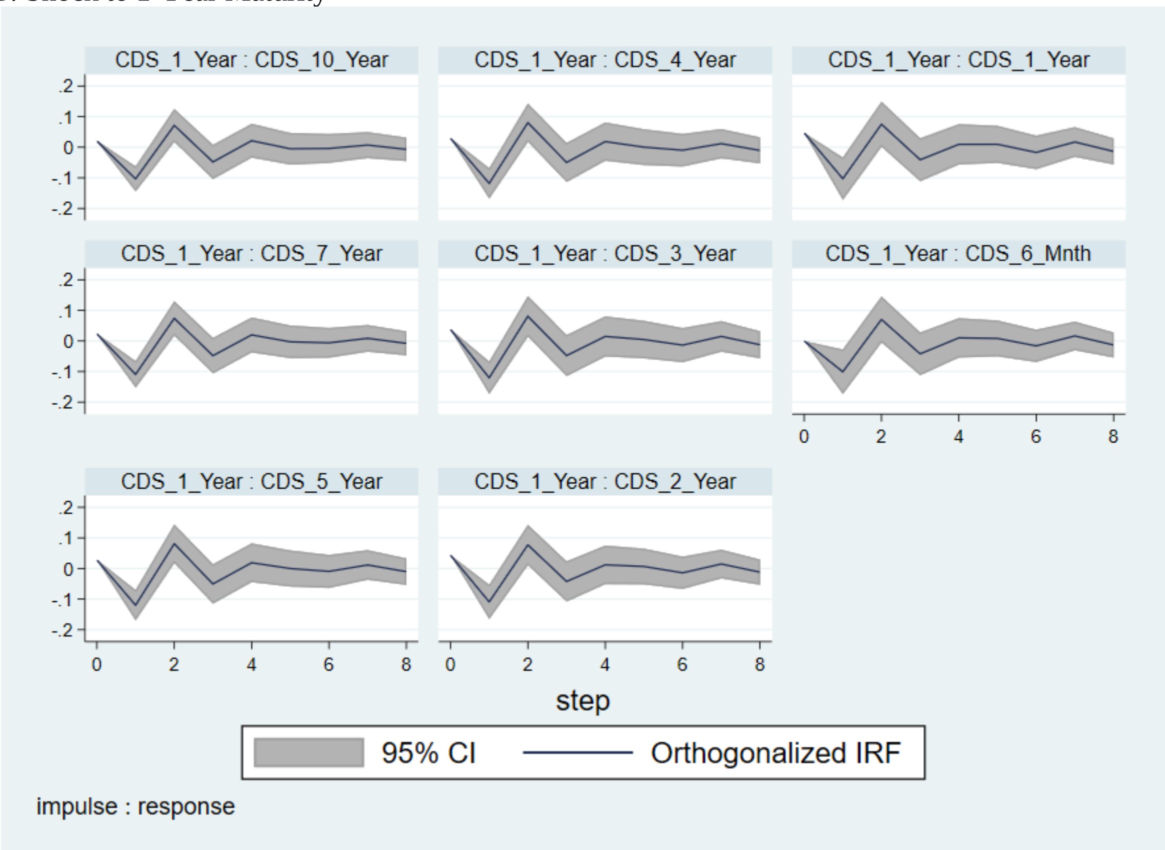
Source: Authors' calculation.

Appendix 1.F: Impulse-Response Functions (IRFs) Graphs.

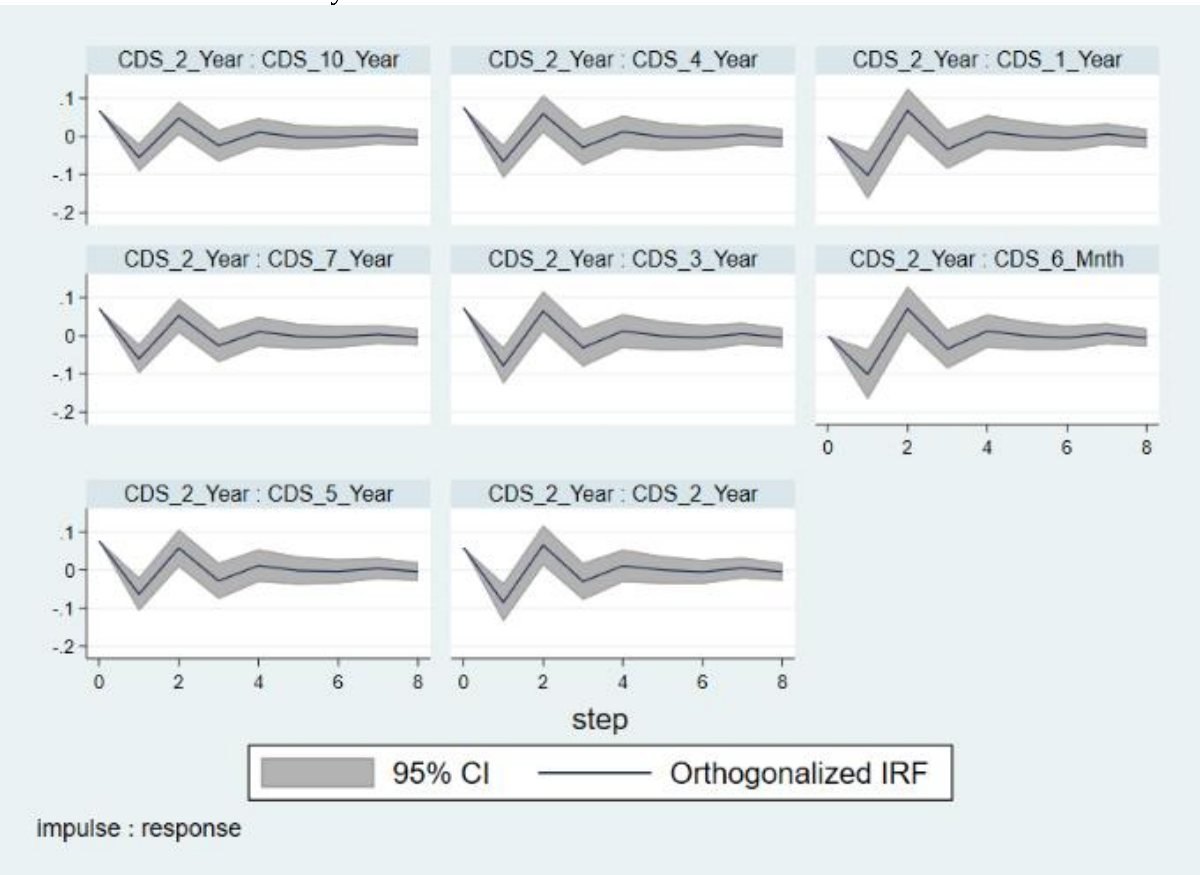
Panel A: Shock to 6-Month Maturity



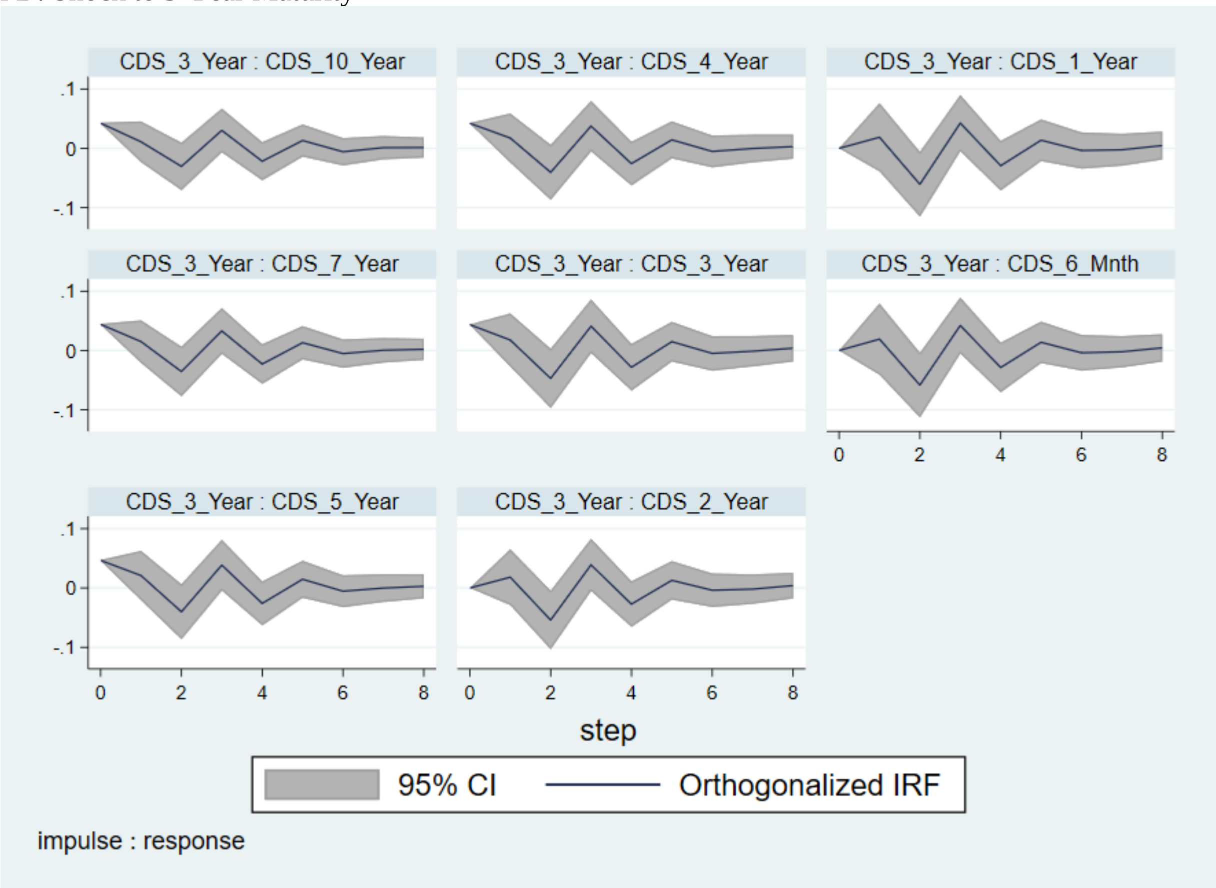
Panel B: Shock to 1-Year Maturity



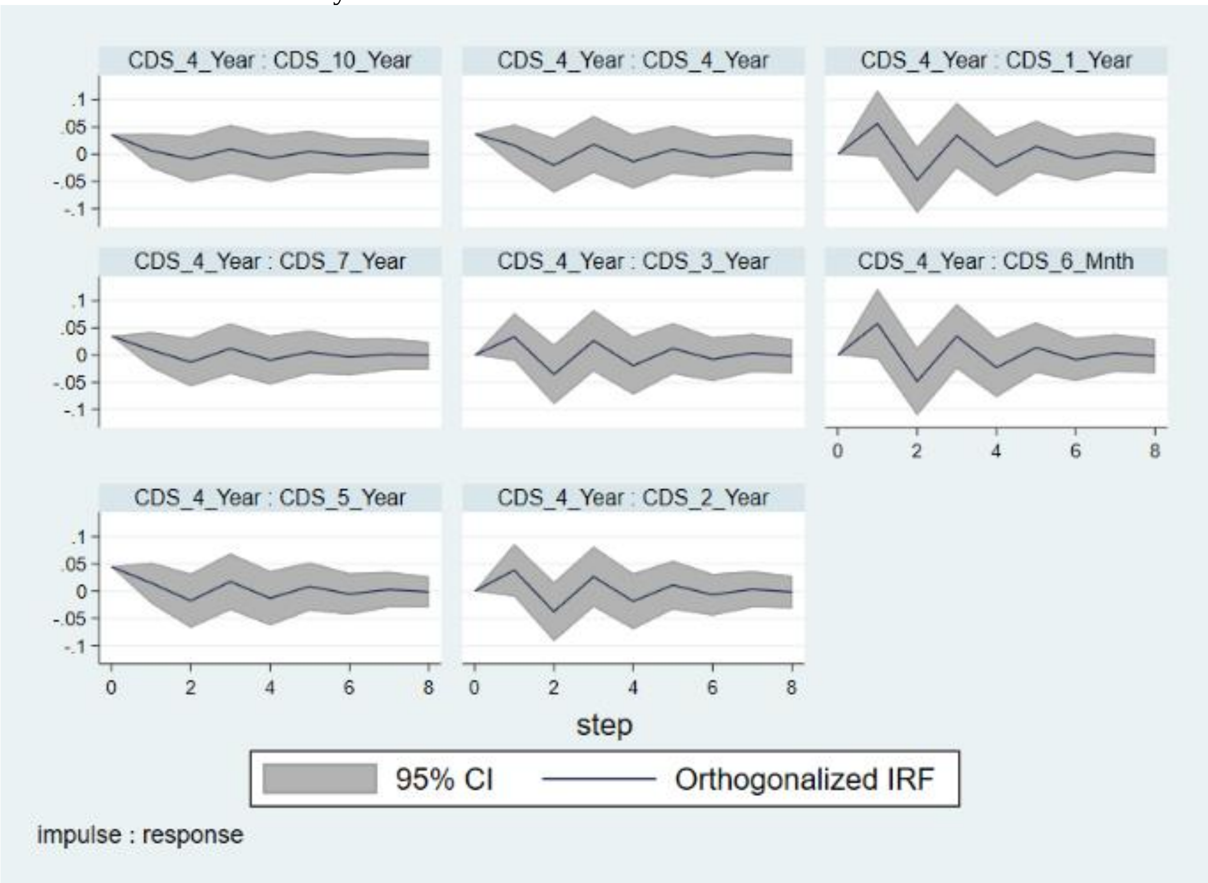
Panel C: Shock to 2-Year Maturity



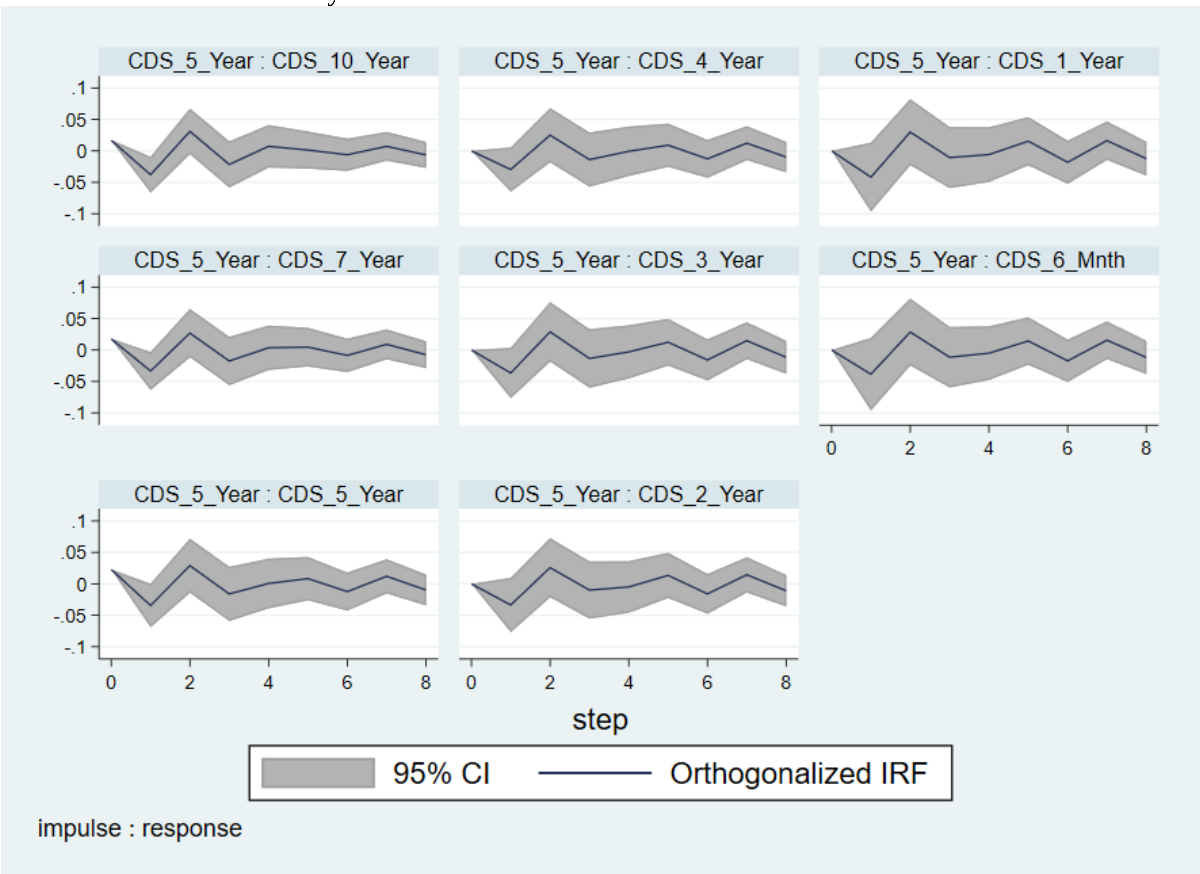
Panel D: Shock to 3-Year Maturity



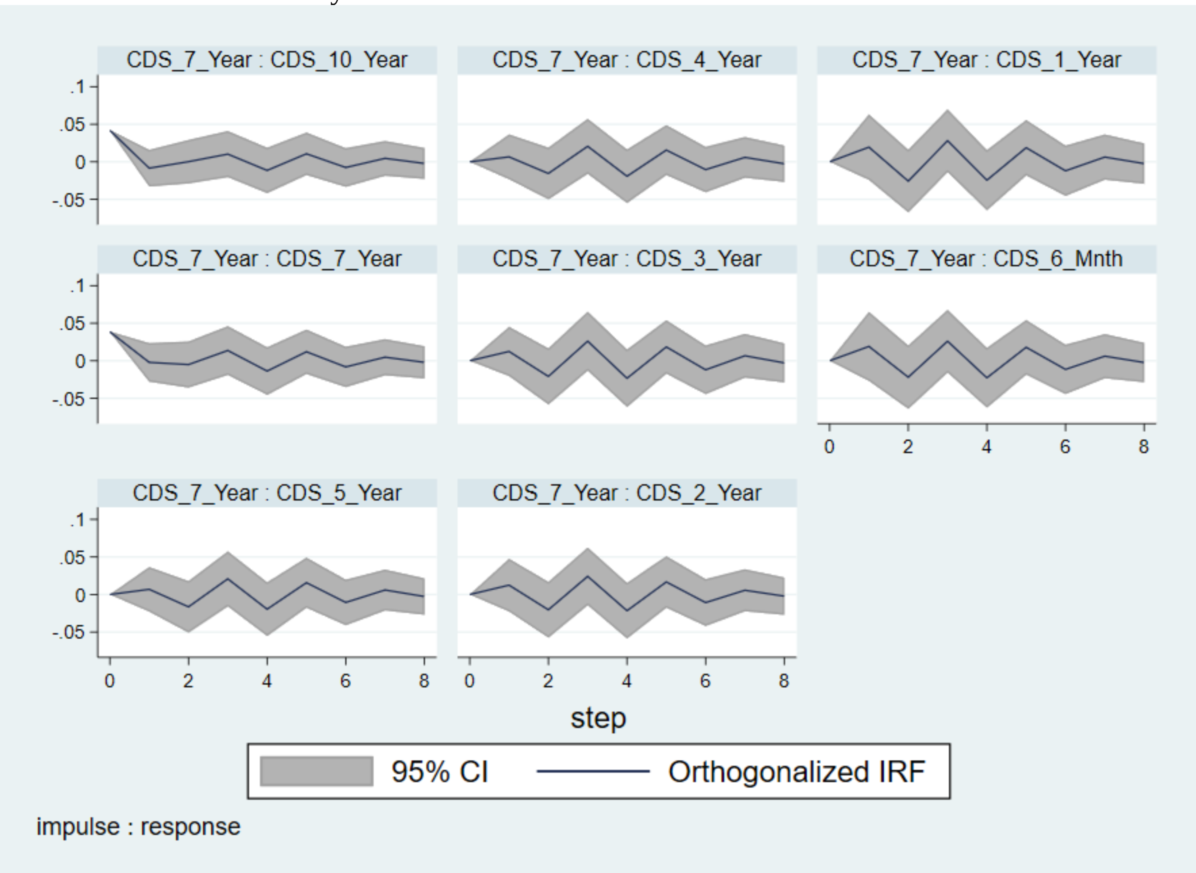
Panel E: Shock to 4-Year Maturity



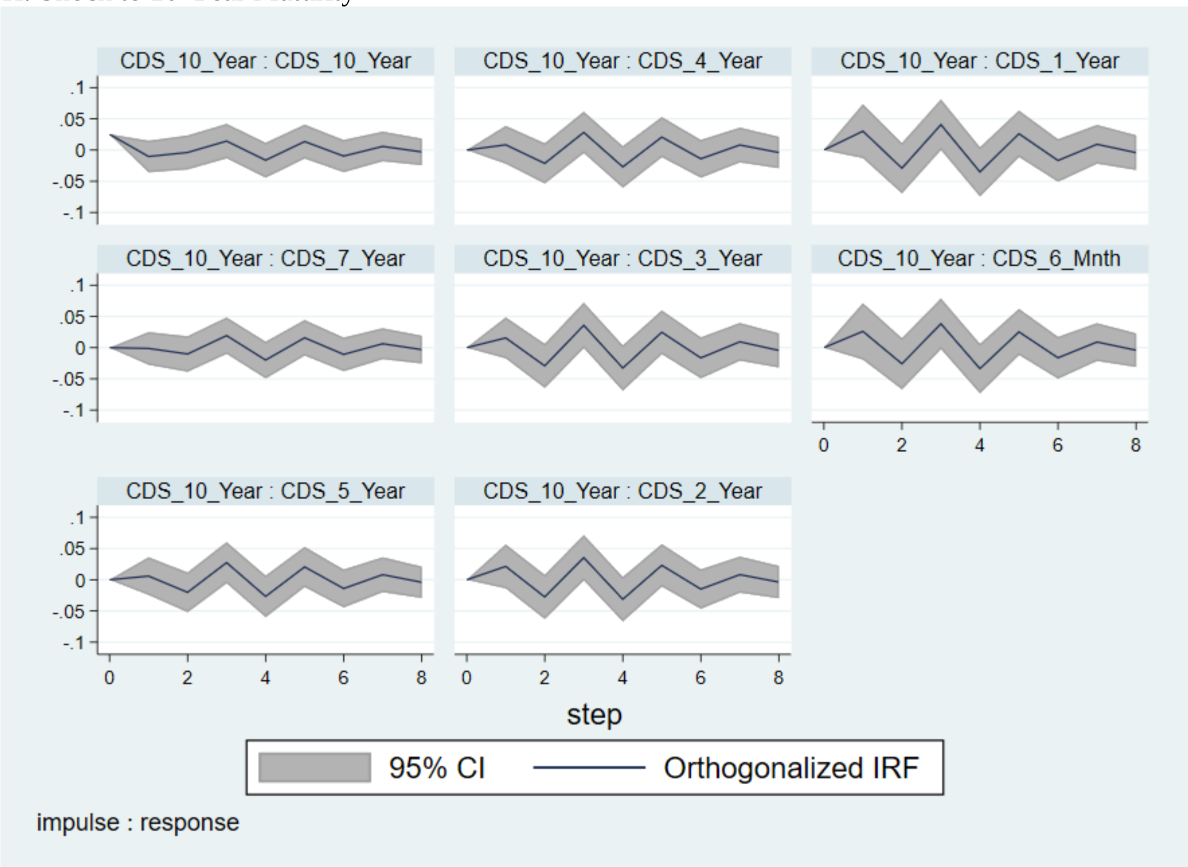
Panel F: Shock to 5-Year Maturity



Panel G: Shock to 7-Year Maturity



Panel H: Shock to 10-Year Maturity



CHAPTER 2 Do CDS Maturities Matter in the Evaluation of the Information Content of Regulatory Banking Stress Tests? Evidence from European and US stress tests.*

* This chapter is based on the article « **Agbodji A.S.S., Nys E. and Sauviat A., 2021, "*Do CDS Maturities Matter in the Evaluation of the Information Content of Regulatory Banking Stress Tests? Evidence from European and US Stress Tests*", Revue économique, Volume 72, January 2021, Pages 65 à 102** », co-authored with Dr. Emmanuelle NYS (Université de Limoges, LAPE) and Prof. Alain SAUVIAT (Université de Limoges, LAPE). We thank the anonymous referees for their constructive comments.
We thank the members of the "Laboratoire d'Analyse et de Prospective Économiques (LAPE)", especially Dr. Ruth Tacneng for their valuable comments and suggestions during the development of this work. An earlier version of the paper was presented at (i) the *36th Symposium on Money, Banking and Finance*, June 12–14, 2019, Besançon (France) and (ii) the *7th Bordeaux Workshop in International Economics and Finance*, November 15, 2019, Bordeaux (France). We therefore thank the participants of these conferences for their advice and suggestions which helped to improve this paper.

2.1. Introduction

A regulatory stress testing exercise is an important banking supervision tool whose main objective is to assess and analyze the resilience of participating banks to hypothetical forward-looking macroeconomic scenarios, including an extreme but plausible stressed scenario. The latter simulates crisis situations (characterized by a recession at the national and global levels, a very high unemployment, etc.) and each of the scenarios is designed over different time horizons (typically 1-year, 2-year, and 3-year time horizons[15]). Overall, the purpose of these tests is to ensure that the participating banking institutions have sufficient financial strength to absorb losses and to remain solvent and strongly capitalized, even in a distressed economic environment. At the end of the test, dozens of data that reflect the evolution of the financial health of each tested bank throughout the different scenarios (including data on solvency, capitalization, market risk, credit risk, liquidity risk, operational risk…) are disclosed in a very detailed way, thus providing to market participants reliable information on the financial strength and resilience of tested banks over different time horizons. To investigate the market response to this disclosure, and thus evaluate the informative value of stress tests, the most suitable instruments available to researchers are Credit Default Swaps (CDSs) since they reflect the market perception of the financial strength of a bank, over different horizons[16].

This paper questions the relevance of using only the 5-year maturity CDS spreads in the evaluation of the informative value of regulatory stress tests. Is the exclusive use of 5-year maturity CDS spreads sufficient to entirely appreciate the reaction of market participants to the disclosure of stress test results? Is it sufficient to fully evaluate the informative content of the disclosed stress test results? To attempt to answer to these questions, we examine whether the market response is the same for all CDS maturities or whether it differs. In other words, we investigate whether short-term maturities of CDS (6-month, 1-year, 2-year, and 3-year maturities) are impacted in the same way as long-term maturities (which include the commonly used 5-year maturity).

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[15] At the beginning of regulatory stress testing exercises, the scenarios implemented had a time horizon of at most 2 years (stress tests until 2011 in Europe, until 2015 in the US).

[16] The CDS market offers a unique opportunity because of the ability to contemporaneously observe multiple instruments that measure the risk associated with the same firm, but at different horizons (Lok and Richardson, 2011).

Our research is motivated by the following. To estimate the market response to the disclosure of regulatory stress test results, and thus evaluate the informative content of this disclosure, the literature almost systematically uses the 5-year maturity CDS spreads (among others, Morgan *et al.*, 2014; Neretina *et al.*, 2014; Flannery *et al.*, 2017; Georgescu *et al.*, 2017 and Ahnert *et al.*, 2018) since it is generally considered to be the most liquid segment of the market (Annaert *et al.*, 2013; Völz & Wedow, 2011). However, one may wonder whether the maturity of 5-year alone can reflect the entire CDS market response. Insofar as the hypothetical forward-looking scenarios of a stress testing exercise have a time horizon of at most 3 years, and since the disclosed results (on participating banks' resilience and financial strength under the scenarios) only cover these 3 years, it can be expected that information provided should be better incorporated into CDS spreads whose maturities are less than or equal to 3 years, compared to CDS spreads of the remaining maturities. These latter can also be impacted but the effect of the disclosure should be better seen on the CDS spreads of short-term maturities (6-month, 1-year, 2-year and 3-year maturities) since these maturities better match the horizon of the stress test scenarios. In other words, we are looking at the short-term because it is the horizon on which information provided are the most robust, relevant and abundant. We therefore suspect a difference in reaction between short-term and long-term CDS maturities. Furthermore, there is another factor that may generate this difference in reaction. In addition to improving the quality and quantity of information available on the situation of tested banks, the disclosure of stress test results also provides valuable information on the ability of these banks to cope with crisis situations, over different horizons (1-year, 2-year, and 3-year). As a result, the spreads of CDS should be impacted differently by this disclosure depending on the CDS maturity, as suggest by Agbodji (2022). More precisely, CDS spreads of short-term maturities should be primarily impacted by the improvement of information available while the impact of information on banks' resilience to possible future shocks should be weak. Indeed, in the short-run, the amount of time that market participants are exposed to possible unexpected economic shocks is small; this may justify a relatively weak impact of new information on the resilience of banks to possible shocks, and a strong impact of new information on their exact situation (Ball and Cuny, 2020). On the other hand, CDS spreads of long-term maturities should be relatively more impacted by information on banks' resilience since market participants are increasingly exposed to economic shocks. As a result, all the spreads, whatever the maturity of CDS, should be impacted by the improvement of information available (the shorter the maturity, the greater the impact). Concerning the information on banks' resilience, short-term CDS spreads should be moderately impacted by the latter and as the CDS maturity increases, this impact should also increase. Overall, the CDS spreads should be impacted differently by the disclosure of stress test results, depending on the CDS maturity.

This makes us suspect a difference in reaction depending on the maturity of the CDS contract, and therefore the impossibility for the 5-year maturity alone to reflect the entire market response. To our best knowledge, no paper has in the past investigated this issue. Our study is therefore important since it examines whether using only the 5-year maturity CDS spreads (following the existing literature) is enough to appreciate the reaction of market participants to the disclosure of stress test results, and entirely evaluate the informative content of this disclosure. Future papers can take this into account when examining future stress tests.

Applying an event study methodology on the tested banks' CDS spreads, we estimate the market response (the Cumulative Average Abnormal Returns CAARs) to the disclosure of the results of ten European and US regulatory stress tests, carried out in the time period from 2009 to 2017. We perform these estimates using daily data on senior CDS spreads and considering each of the eight CDS maturities (6-month, 1-year, 2-year, 3-year, 4-year, 5-year, 7-year, and 10-year maturities) in order to examine whether or not the market response is the same from one maturity to another.

Our empirical results show that this is not the case. For a given stress test, the impact of the disclosure varies from one maturity to another since the CAARs estimated using the different CDS maturities differ substantially. For the same test, market participants may react strongly on one maturity (very high CAARs in absolute value) and weakly on another one (very low CAARs in absolute value) after the disclosure. More precisely, we evidence that for a given stress test, the nature of the reaction (*upward* or *downward* reaction) is the same for all CDS maturities while its extent (magnitude) differs substantially from one maturity to another. This suggests that with the new, reliable and relevant information provided, market participants reassess the default risk of participating banks over different horizons and adjust accordingly their corresponding spreads of CDS, at the level of the different maturities. According to our findings, this adjustment (which is *de facto* the market response to the disclosure) differs depending on the CDS maturity considered, so on the horizon. We therefore support that the information provided is useful for all maturities of CDS, not just for the 5-year maturity. In general, it impacts differently spreads of CDS depending on whether one consider short-term or long-term CDS maturities. Therefore, examining the informative value of regulatory stress tests by using only the 5-year maturity CDS spreads is not sufficient because it leads to incomplete and partial results. This, in turn, can lead to misinterpretations of the informative content of stress test results, and therefore, an incorrect appreciation of the effectiveness of regulatory stress tests.

Being the first to perform such empirical investigations, our paper attempts to contribute to the existing literature on regulatory banking stress tests, more precisely the literature on the impact, the informative value and the effectiveness of stress tests (Petrella and Resti, 2013; Morgan *et al.*, 2014; Neretina *et al.*, 2014; Flannery *et al.*, 2017; Georgescu *et al.*, 2017 and Ahnert *et al.*, 2018). It attempts to further develop the understanding of the market response to a stress testing exercise. Secondly, our paper also contributes to the strand of the literature on banking opacity (among others, Flannery and Houston, 1999; Jordan *et al.*, 2000; Morgan, 2002; Flannery *et al.*, 2010) since we evidence that following the disclosure of stress test results, market participants, considering the new relevant information provided, corrects (adjusts) the CDS spreads of participating banks at the level of all maturities. This correction from the market highlights the existence of a banking opacity, i.e. the impossibility for market participants to have access to reliable financial data on banks. Our paper finally contributes to the debate on transparency in banking supervision (Jordan *et al.*, 2000; Dudley, 2009; GAO, 2010 and Goldstein and Sapra, 2013) since our results show that more disclosure about the banks' situation and resilience can help market participants to better assess the value and the risks of banks and thus, to better discriminate them.

The remainder of our paper is organized as follows. Section 2.2 reviews the relevant literature on regulatory banking stress tests. In Section 2.3, we first present a brief overview of the regulatory stress tests that we consider. We then describe the sample, the data and the empirical methodology employed to perform our investigations. The presentation of the results follows in Section 2.4 which also includes several robustness tests and a discussion of our findings. Finally, Section 2.5 concludes the paper.

2.2. Related Literature

Banks are intrinsically opaque because of their intermediation function. Investors and savers place their money in banks which are supposed to lend to borrowers after a rigorous screening, and with an intensive monitoring (Diamond, 1984). But the risks taken by banks in this intermediation process are hard to observe for investors and savers. Indeed, if banks were completely transparent, there should be no market reaction to the release of supervisory information; but it is not the case since the release of such information induce substantial and significant movements in stock prices (Berger and Davies, 1998; Flannery and Houston, 1999; Jordan *et al.*, 2000). Therefore, several empirical papers have been interested in the impact and the informative value of regulatory banking stress tests. Almost all of them examines at least the stock market reaction around these stress tests' key event dates but there is an emerging literature on the effects of regulatory stress tests on CDS performance.

Morgan *et al.* (2014) for example were interested in the 2009 US SCAP effects. Using a standard event study methodology, they investigate whether this latter produced useful and valuable information for the market by considering two groups of banks: the GAP banks and the NO GAP banks[17]. In summary, they show that the test provided useful information to the market. More precisely, they evidence that prior to the test, financial markets were largely able to identify the banks without capital gaps and those which are under-capitalized; what they didn't know was the exact amount of capital required for under-capitalized banks. Therefore, at the results' disclosure, the market was surprised and reacted significantly by correcting banks' stock prices (which increased) and spreads of CDS. These latter decline, particularly for undercapitalized banks whose spreads fell by 59 basis points relative to spreads for

[17] The GAP banks are those with capital gaps while the NO GAP banks are those without capital gaps.

NO GAP banks. Based on the US banking stress tests from 2009 to 2015 (SCAP, CCAR and DFAST), Neretina *et al.* (2014) complement the work of Morgan *et al.* (2014) by reassessing their findings and investigating whether their conclusions are also valid for other stress tests. In contrast with Morgan *et al.* (2014) findings, they show that the disclosure of the 2009 US SCAP results had no effect on equity returns. But they evidence on the other hand a decline in CDS spreads, especially for NO GAP banks (with an average CAR of -55,43 basis points). For the stress tests carried out after the SCAP, they find evidence that CDS spreads declined in response to the publication of stress test results only in 2012 and 2013.

Then, Flannery *et al.* (2017) examine changes in banks' stock prices, trading volumes and CDS spreads around several disclosure dates of regulatory stress test results in the US, in the time period from 2009 to 2015. Unlike previous studies, they don't use a standard event study methodology since they argue that this latter is not suitable for measuring the true informative value of a stress testing exercise because of inappropriate assumptions embedded in it. Using their "customized" event study methodology, they show that the nine tests produce new and valuable information not only about stress-tested banks' situation, but also about non-stress-tested banking companies; the tested sample's reaction almost always exceeding the one of the non-stress-tested sample. More precisely, using an absolute cumulative abnormal CDS Spread (|CACDS|), they evidence that the CDS spreads of stress tested banks change abnormally and significantly around all the stress test disclosure dates considered (especially around the 2009 SCAP disclosure date). Then considering respectively the tested and the non-tested banks' group average |CACDS|, they highlight significant differences between them thus confirming the fact that the response of the tested sample almost always exceeds the one of the non-stress-tested sample.

Like in the US, European banking authorities have also performed several regulatory stress testing exercises since 2009 and many empirical papers have been interested in the effects of their results' disclosure on CDS markets.

Georgescu *et al.* (2017) try to determine empirically if European regulatory stress tests are really useful (if they provide new and valuable information to the market), basing on the 2014 and 2016 EBA-ECB stress tests. They therefore assess the reaction of market participants by estimating the cumulative abnormal returns (CAR) using tested banks' CDS MID spreads and stock prices, and sovereign CDS MID spreads. For these estimates, they employ an event study methodology, around several event dates (e.g. announcement dates, disclosure dates etc...). With somewhat mixed results, they argue that stress tests provide new information to the market. More precisely, they find that new and useful information was revealed to the CDS market participants around the announcement of the test (only in 2014), the announcement of the key features (in 2014 and 2016) and following the results' disclosure (only in 2016); new information that was immediately integrated in tested banks' CDS spreads as reflected in statistically significant abnormal CDS returns. Authors also find that the publication of stress test results allows markets to better discriminate between "good" (strong) banks and "bad" (weak) banks. Indeed, authors show that under the adverse scenario, banks that lost a large part of their Common Equity Tier 1 ratio (what prove their weakness) were been punished by the market; following the results' disclosure, these latter reported significantly higher positive abnormal CDS returns compared to better performing banks. Similarly, analyzing the impact of stress testing results' publication on bank's equity and CDS performance, Ahnert *et al.* (2018) also come to the same conclusion. Indeed, performing their empirical investigations on a larger number of regulatory stress tests (ten tests including six US CCAR and four EBA/ECB stress tests in the time period between 2010 and 2017), authors show that the results' disclosure provide new information to market participants and reduce bank opacity by improving the quality and the quantity of information available on tested banks' situation. Hence, it allows markets to better discriminate between strong banks (which were rewarded) and weak banks (which were sanctioned). Indeed, they highlight that following the results' release, strong banks have better funding costs and higher stock prices unlike weak ones. More precisely, they show that banks that passed the test show significant and positive abnormal stock returns and smaller CDS spreads (with an abnormal CDS returns of -83 basis points). In contrast, those that failed experience significant and negative abnormal stock returns and higher CDS spread (172 basis points). Concerning the announcement date, they find that banks that are announced to be stress tested surprisingly experience on average wider CDS spreads (78 basis points of abnormal CDS returns). Performing finally a multivariate regression analysis, they evidence that bank's asset quality and return on equity are significant predictors of the pass/fail outcome of a bank during a stress test.

Overall, to examine the market response to the disclosure of stress test results, and the informative content of this disclosure, all the above papers use either stock prices or the 5-year maturity CDS spreads, with somewhat mixed findings which may be due to the use of inappropriate instruments. On the one hand, stress tests provide to market participants reliable information on whether or not tested banks have sufficient financial strength to absorb losses and to remain solvent and strongly capitalized, over different time horizons. On the other hand, CDS spread appears to be a relatively pure pricing of the bank default risk (Zhang *et al.*, 2009), over different horizons since there are eight different maturities of CDS. Hence, the information provided by stress tests over different horizons appears to be what the CDS spreads reflect, over different horizons. This makes CDSs of different maturities, the most suitable instruments to use when examining the informative value of stress tests, compared to bonds or stocks.

Bonds also have different maturities but CDS instruments have major advantages over the latter (and stocks). First, as shown by Blanco *et al.* (2005), CDSs lead the bond market in price discovery. In other words, compared to bond spreads, CDS spreads appear to react more accurately and rapidly to new information regarding the underlying reference entity, especially in the short run. According to Zhang *et al.* (2009), this could be partly attributed to the fact that CDSs are unfunded and do not face short-sale restrictions. This is a key advantage for our empirical investigations since using an event study methodology, we attempt to capture banks' abnormal performances over a relevant and short window around the disclosure date. Second, the maturities of the CDS contracts are strictly standardized (they are the same across banks) and fixed over time, unlike bond contracts' maturities which are not uniform across firms and varies a lot over time (Han and Zhou, 2015). Since our investigations are based on a group of tested banks, this also represents a key advantage for our empirical investigations. Furthermore, the existence of different standardized maturities is also one of the main advantages of CDSs compared to stocks whose prices only indicate the current value (risk) of the reference entity. Third, CDS spreads are directly observable unlike bond spreads which have to be calculated using a benchmark risk-free yield curve (Ericsson *et al.*, 2006; Longstaff *et al.*, 2005). However, the choice of the risk-free reference asset may be problematic (Houweling and Vorst, 2005). All these advantages further support the consideration of CDSs as instruments, rather than stocks or bonds. This paper therefore uses all the different maturities of CDS to examine the market response to the disclosure, and evaluate the informative content of this disclosure.

2.3. Sample, Data, and Methodology

In this section, we first present the different (US and European) regulatory stress tests that we consider for our investigations. Then, we describe respectively the sample on which this study is based, the data used to perform our investigations and the methodology employed to estimate the market reaction. Finally, we analyze the liquidity of the CDS market for the different maturities using our CDS spreads data. Indeed, since the 5-year CDS contracts are generally considered to be the most liquid segment of the CDS market, we were interested in the liquidity of the remaining segments before performing our estimations.

2.3.1. Regulatory Stress Testing Exercises in Europe and the United States

To perform our empirical investigations on the market response to stress test results' disclosure, we consider all relevant regulatory stress tests carried out in Europe and in the US, from 2009 to 2017.

In Europe, five stress testing exercises were carried out during this period. The first and the second ones that took place respectively in 2009 and 2010 was conducted by the Committee of European Banking Supervisors (CEBS)[18]. The next one was conducted in 2011 by the European Banking Authority (EBA), on the same sample of banks as the 2010 test. The remaining tests were also performed by the EBA,

[18] The 2009 CEBS stress test was conducted on a sample of 22 major European cross-border institutions representing on a consolidated basis, 60% of the total assets of the EU banking sector. At the end of the test, supervisors did not disclose the names of the 22 participating banks, nor the detailed results of the test. The 2010 and 2011 exercises were conducted on a sample of 91 European banks representing together 65% of the total assets of the EU banking sector. Unlike the 2009 test, details data on each tested bank were disclosed at the end of these two tests.

respectively in 2014 and 2016[19] in close cooperation with the European Central Bank (ECB) within the Single Supervisory Mechanism (SSM). Among these five tests, we will not consider the 2009 one in our study since its aim was not to assess banks individually, but to evaluate the resilience of the European banking industry as a whole, without publishing the participating banks' names.

In the US, the first regulatory stress test was the 2009 Supervisory Capital Assessment Program (SCAP). Nineteen US bank holding companies (representing two-thirds of the US banking system's assets) participated in this test which was unprecedent in terms of supervisory information disclosure. Since then, the Federal Reserve (FED) formally introduced a regulatory framework to annually assess, regulate, and supervise US Bank Holding Companies (BHCs). This supervisory assessment consists of two related programs: The Comprehensive Capital Analysis and Review (CCAR) and the Dodd-Frank Act stress tests (DFAST). The first program involves both a qualitative and a quantitative evaluation. More precisely, the FED performs for each participating BHC a qualitative analysis of its internal capital planning processes and governance, and a quantitative assessment of its capital positions (capital adequacy). In the other side, like the SCAP, the DFAST program examines how banks' capital levels would evolve under baseline, adverse and severely adverse economic conditions (stressed period) in order to assess their ability to absorb possible future shocks. The first CCAR took place in 2011 while the first DFAST took place in 2013[20].

For the US, this study focuses on the DFAST program as it is the one that assesses banks' financial strength under hypothetical forward-looking scenarios (like the SCAP and all European tests), unlike the CCAR program. In addition, the results of the DFAST stress tests are disclosed approximately a week before the corresponding CCAR results.

[19] The 2014 stress test includes 123 European banking groups (representing more than 70% of the EU banking industry assets) while the 2016 exercise was carried out on a sample of 51 banking groups. The results of these two tests were also disclosed in a very detail way.

[20] The 2013, 2014 and 2015 DFAST was performed respectively on 18, 30 and 31 bank holding companies (BHCs). In 2016, 33 BHCs participated in the DFAST while they were 34 for the 2017 exercise.

2.3.2. Capturing the CDS Market Response to Stress Test Results Publication.

2.3.2.1. Sample Selection and Data Description

Our initial sample includes all the banks that have been tested in at least one of our considered stress tests. More precisely, the US initial sample includes 34 banks that have been tested at least once by the Federal Reserve between 2009 and 2017. The European sample is comprised of 123 banks (across 22 EU countries) that have been tested by the CEBS (in 2010) and/or the EBA (in 2011, 2014 and 2016).

Then, to perform our investigations, we collect daily data on senior CDS spread from the Bloomberg terminal, for each of the participating banking institutions in our initial sample and for all maturities. We get these data exclusively from the CMA New York source, which provides closing bid and ask CDS quotes. However, CDS spreads data are not available for all banks; for some of them, tradable CDS doesn't exist while it exists for others but with no available data. At the end, in our US final sample, the number of tested banks with available information on tradable credit default swap range from 9 to 12 per stress test. Considering the 2009 SCAP, the number of banks in the sample used to estimate the market response is 9. For the 2013, 2014, 2015 and 2016 DFAST, this number is 11 while it is 12 for the 2017 DFAST. More importantly, for each of these tests, the sample of banks is the same from one maturity to another. In Europe, the number of tested banks with available information on tradable CDS varies from 33 to 50 per stress test. Considering the EBA test of 2016, the number of banks in the sample used to estimate the market response is 33 and this sample is the same from one maturity to another. But for each of the remaining tests (tests of 2010, 2011 and 2014), the number of banks differs very slightly from one maturity to another because of missing data. Therefore, as robustness check (section 2.4.3.4), we re-estimate the market reaction by removing banks that have missing data on one or more maturities, so that we have the same sample of banks from one maturity to another. The results show that there are almost no differences between our findings and the new estimations. All of these companies are banks, with the exception of 2 US companies[21] which belongs to the "Diversified Financial Services" industry. Appendix 2.A

[21] Ally Financial Inc. and American Express Co.

provides an overview of the banks included in our final sample, test by test in the US (Panel A) and in Europe (Panel B). These two panels also provide for each test, the share of the total assets of banks included in our study sample compared to that of banks covered by the stress test. These shares (more than 81% on average in the US and in Europe) show that banks included in our empirical analysis are representative of total assets of tested banks. Panel C shows the different countries represented in the EU final sample with the number of banks per country.

As Indices for bank CDS, following Morgan *et al.* (2014), Neretina *et al.* (2014), Flannery *et al.* (2017) and Ahnert *et al.* (2018), we employ the *Markit CDX North America Investment Grade Index* for the US. For Europe, we use the *Markit iTraxx Europe Investment Grade index*. Both are composed of 125 equally weighted credit default swaps on US (European) investment grade entities, distributed among several sub-indices (Financials, Non-Financials and High Volatility). We then collect daily data from the Bloomberg terminal (CMA New York source) for each of these two indexes, but not for all maturities. Indeed, only four maturities are available (3, 5, 7 and 10 years). Therefore, we compute the 4Y daily CDX spreads for each index by taking the average between the 3Y and the 5Y CDX spreads, at the level of each date. For the remaining unavailable maturities (6-month, 1-year and 2-year), we assigned them the spreads of the nearest available maturity to perform our investigations (so the spreads of the 3-year maturity).

2.3.2.2. Research Design and Methodology

In order to investigate whether the market response differs depending on the CDS maturity considered, we employ an event study methodology (described for example in Brown and Warner (1985) and Campbell, Lo, and MacKinlay (1997)) that has been extensively used in the regulatory stress test literature.

More accurately, to capture the CDS market reaction to the publication of a given stress test results, we compute the Cumulative Average Abnormal (CDS) Returns CAARs of the group of tested banks over a relevant window around the disclosure date ("event window"); the CAARs being an estimation of the impact of the stress test outcomes' publication on the group of participating banks' spreads.

Then, to check whether the market reaction is the same from one maturity to another, we estimate for each stress test eight different CAARs considering each of the eight CDS maturities. In other words, we apprehend the response of the market using not only the 5Y maturity data (as previous papers), but also all the remaining maturities data in order to highlight possible differences in reactions depending on the maturity considered.

2.3.2.2.1. Events and Event Dates

In our study, for a given stress test, we consider as "event" the disclosure of its results. Following (among others) Flannery *et al.* (2017) and Ahnert *et al.* (2018), we will not consider as "event date" the stress test results' publication date but rather the next trading day. Indeed, the results are published either on a trading day but after market closing (in the US as in Europe), or during a non-trading day (as it was the case for the 2014 ECB-EBA stress test). Therefore, analytically, the actual event date is not the results' publication date, but rather the following trading day. Table 2.1 reports, for each stress testing exercise, the results' disclosure date and the corresponding event date in the US (Panel A) and in Europe (Panel B).

Table 2.1: The disclosure date of stress test results and the corresponding event date in the US and Europe.

Panel A: Timeline of regulatory stress test disclosures in the US (2009–2017)

Stress Test	Release Date	Event Date
2009 SCAP	Thursday May 7, 2009	Friday May 8, 2009
2013 DFA Stress Test	Thursday March 7, 2013	Friday March 8, 2013
2014 DFA Stress Test	Thursday March 20, 2014	Friday March 21, 2014
2015 DFA Stress Test	Thursday March 5, 2015	Friday March 6, 2015
2016 DFA Stress Test	Thursday June 23, 2016	Friday June 24, 2016
2017 DFA Stress Test	Thursday June 22, 2017	Friday June 23, 2017

Source: U.S. Federal Reserve (FED) and Authors' calculation.

Panel B: Timeline of regulatory stress test disclosures in Europe (2009–2017)

Stress Test	Release Date	Event Date
2010 EU-wide Stress Test	Friday, 23 July 2010	Monday, 26 July 2010
2011 EU-wide Stress Test	Friday, 15th July 2011	Monday, 18 July 2011
2014 EU-wide Stress Test	Sunday, 26 October 2014	Monday, 27 October 2014
2016 EU-wide Stress Test	Friday, 29 July 2016	Monday, 01 August 2016

Source: European Banking Authority (EBA) and Authors' calculation.

2.3.2.2.2. Estimating the Cumulative Average Abnormal (CDS) Returns

To obtain the CAARs of a group of banks over an event window, we measure first of all the abnormal return $AR_{i,t}$ of each bank i in this group, on each date t of the event window. The abnormal return is the difference between the observed (actual) CDS spread return R_{it} and an expected (normal) return $\hat{R}_{it}$. This latter is the return that would be expected if the event did not take place. To estimate it, following the recent stress test literature (Campbell *et al.*, 2010; Morgan *et al.*, 2014; Neretina *et al.*, 2014; Flannery *et al.*, 2017 and Ahnert *et al.*, 2018), we use a single-factor market model[22] (equation 1) over a 120-trading days window (consistent with MacKinlay (1997) suggestion and following Alves *et al.*, 2015; Flannery *et al.*, 2017 and Ahnert *et al.*, 2018). Furthermore, since the stress testing exercises are generally performed each year (especially in the US), the choice of a 120-trading days estimation window allows us to prevent previous test events from influencing the estimation of the normal performance model parameters. The estimation window ends 10 trading days before the event as it goes from t-130 to t-11, t being the event date to be tested.

$$R_{i,t} = \alpha_i + \beta_i . R_{m(i),t} + \varepsilon_{i,t} \tag{1}$$

Therefore, the abnormal return or residuals $AR_{i,t}$ of a bank i, on date t is given by:

$$AR_{i,t} = R_{i,t} - [\ \hat{\alpha}_i + \hat{\beta}_i (R_{m(i),t})\ ] \tag{2}$$

[22] Some papers on the same topic used a two or three-factor model to control for external factors. However, Ahern (2009) show that multifactor models produce only marginal benefits over a one-factor market model in predicting event day normal returns. This motivated us to use a one-factor market model, like previous papers.

Following the work of Morgan *et al.* (2014), Flannery *et al.* (2017) and Ahnert *et al.* (2018), we compute $R_{i,t}$ ($R_{m(i),t}$) by transforming CDS (CDX) spreads into logarithmic returns with:

$$R_{i,t} = log(\frac{S_{i,t}}{S_{i,t-1}}) \quad \text{and} \quad R_{m(i),t} = log(\frac{S_{m(i),t}}{S_{m(i),t-1}}) \tag{3}$$

Where:

$R_{i,t}$ is the daily CDS spread return of bank i, on day t and $R_{m(i),t}$ the daily CDX spread return of bank i's index, on day t. $S_{i,t}$ is the daily CDS MID spread of bank i, on day t when $S_{m(i),t}$ is the daily CDX MID spread of bank i's index, on day t[23]. $\hat{\alpha}_i$ and $\hat{\beta}_i$ are respectively the Ordinary Least Squares estimates of α_i and β_i. As we can see, α and β are estimated separately for each bank i.

Then, since we are working on a pool of banks, we compute in a second stage the Average Abnormal Returns (AAR_t) which is the average of participating banks' abnormal returns on date t.

$$AAR_t = \frac{\sum_{i=1}^{N} AR_{i,t}}{N} \tag{4}$$

Where N is the number of stress tested banks. We perform this computation for each date of the event window.

We focus on a three-day event window including the event date and the two following days (t, t+1, t+2). Indeed, the use of a narrow window of three days, without taking into account pre-event dates (t-2 and t-1) allows reducing contamination problems which may bias the results of the analysis. In addition, this window incorporates the possibility that investors need time to properly assimilate all the implications of information revealed[24], or that they react slowly to this information. Effectively, Krivin *et al.* (2003) show that the larger the surprise the longer it will take, for the market, to fully impound the information in the announcement.

[23] The MID spread of CDS (CDX) corresponds to the average between the BID and the ASK CDS (CDX) quotes.

[24] For each of the scenarios of a stress test, thousands of data that reflect the financial health of each participating bank throughout the (simulated) crisis situations are disclosed in a very detailed way.

Finally, we calculate the Cumulative Average Abnormal (CDS) Returns CAARs by summing the Average Abnormal Returns AAR_t over our event window.

$$\text{CAAR}\ (t_0, t_1, t_2) = \sum_{t=t_0}^{t_2} \text{AAR}_t \tag{5}$$

Statistical significance of CAARs

After estimating a CAARs, we perform several significance tests in order to establish its statistical validity. In other words, we compute and analyze several statistics in order to “attest” whether the Cumulative Average Abnormal Returns that we estimated are significantly different from zero (and thus not the result of pure chance) or not.

A vast literature exists on significance tests in event study methodology. These latter can be categorized into two groups: parametric and non-parametric tests.

Parametric tests are based on the traditional t-test and rely on specific assumptions about the population parameters (normal distribution of CDS spreads in our case). To establish the statistical significance of our computed CAARs, we use three of them that, according to us, are the most relevant for our study.

The first one is **the standardized abnormal return test** developed by **Patell** (1976) who tried to adjust the classic t-test by standardizing the event window's ARs. However, many papers show later that a variance (volatility) increase on the event date can seriously bias the Patell test (among others, Brown and Warner, 1980, 1985)[25]. Therefore, Boehmer, Musumeci and Poulsen (1991) improve this latter by developing **the standardized cross-sectional test** (**BMP test**) which is robust to possible event-induced volatility and thereby outperforms the Patell test (Higgins and Peterson, 1998; Graham, Pirie and Powell, 1996; Harrington and Shrider, 2007; Campbell, Cowan and Salotti, 2010; Marks and Musumeci, 2017). It is widely considered as the default parametric test (Marks and Musumeci, 2017; Cowan, 2017). Nonetheless, it does not account for possible cross-sectional correlation of abnormal returns which can arise when all banks experience the event on the same date. To overcome this problem,

[25] More recently, Marks and Musumeci (2017) find that even under ideal conditions when the event creates no additional variance, the Patell test remains biased.

Kolari and Pynnonen (2010) propose an adjustment of the BMP test that will account for cross-sectional correlation. It is the **Kolari-Pynnonen test** (or **the adjusted standardized cross-sectional test**).

However, since these three parametric tests assume that CDS spreads returns are normally distributed, they may underperform if this assumption is no longer respected. Hence, to avoid this situation, we compute in addition two non-parametric tests that are not relied on any underlying assumptions. These tests are particularly important in our study since CDS spreads are not normally distributed (right-skewed distribution).

Investigating the accuracy and power of statistical tests applied to one-factor market model abnormal returns (with a single-market sample), Campbell, Cowan and Salotti (2010) find that **the Cowan (1992) Generalized Sign test** and the Corrado (1989) rank test are more powerful than two commonly used parametric tests, namely the BMP test and the Crude Dependence Adjustment CDA test (Brown and Warner; 1980, 1985). We therefore use as non-parametric test, the Cowan (1992) Generalized Sign test following Harvey *et al.* (2004), among others. Based on the rank testing approach of Corrado (1989) and Corrado and Zivney (1992), Kolari and Pynnonen (2011) developed the "so-called" **generalized rank (GRANK) non-parametric test** which is, to our best knowledge, the most reliable and powerful test available. It dominates all parametric tests as well as the Corrado (1989) and the Corrado and Zivney (1992) rank tests (Kolari and Pynnonen, 2011). Consequently, it will be our second non-parametric test.

All the (event study) calculations and estimations are done using the "Eventstudy2" module in STATA (Kaspereit, 2019).

2.3.3. Liquidity and Summary Statistics of CDS Spreads

2.3.3.1. Liquidity of Spreads of CDS

Liquidity in the CDS market reflects the ease with which traders can initiate a contract at an agreeable price (Tang and Yan, 2007). As mentioned above, most of the papers that were interested in the response of the CDS market (following stress tests) performed their investigations based solely on the 5-year maturity CDS contracts since these latter are generally considered in the literature to be, by far, the most liquid segment of the CDS market. However, since this study is concerned with the market response at the level of all CDS maturities (not just the maturity of 5-year), we first focused on the liquidity of our data. Specifically, before starting our event studies, we first analyze the liquidity of CDS spreads of each maturity both at the bank level and at the index level.

It is difficult to find a single summary measure to capture the various facets of liquidity (adverse selection, search frictions, inventory costs...). Hence, to measure (estimate) the liquidity of CDS contracts, following Tang and Yan (2013), Annaert *et al.* (2013) and Samaniego-Medina *et al.* (2016), we use the Bid-Ask spread of the CDS quotes, i.e. the difference between ask and bid quotes. Our choice to use the bid-ask spread is primarily motivated by the fact that it is arguably the most widely used CDS liquidity proxy in finance. In addition, according to Bongaerts *et al.* (2011) and Tang and Yan (2010), there are significant correlations between the bid-ask spread and other liquidity proxies (e.g., number of quotes per CDS, data on trades or volume of orders). Following Samaniego-Medina *et al.* (2016) and Arakelyan and Serrano (2016), we consider the absolute bid-ask spread (rather than the relative one) that we compute on a daily basis. According to Pires *et al.* (2011) and Coro *et al.* (2012), the absolute bid-ask spread is already a proportional measure. As liquidity increases, the size of the bid-ask spread narrows.

Table 2.2 provides the summary statistics of the absolute bid-ask spreads, for all CDS maturities, and at the level of each year of our study period. Panel A applies to the EU sample (period from 2009 to 2016) while Panel B applies to the US sample (period from 2009 to 2017). Following Agbodji (2022), we calculate a "BAS Ratio" statistic which, at the level of a maturity, is the average bid-ask spread of the latter divided by that of the 5-Year maturity. This will allow us to compare the liquidity of the different maturities with each other. A BAS Ratio equal to one means that the corresponding maturity is as liquid as the 5-year maturity. When higher (lower) than one, this means that the maturity is less (more) liquid than the 5-year maturity.

Panel A shows that over the period from 2009 to 2013, the most liquid maturities are that of 10-year, 7-year and 5-year since their BAS Ratio is equal to or very close to one, while that of the remaining maturities varies on average from 1,83 (in 2009) to 1,60 (in 2013). In general, over this period, higher maturities are the most liquidity. However, over the period from 2014 to 2016, the difference between the maturities in terms of liquidity has narrowed considerably. More precisely, whatever the maturity considered, the BAS Ratio is either equal to one or close to one, especially in 2015 and 2016 where the average BAS Ratio (when considering all maturities) is 1,07. Overall, from 2009 to 2016, Panel A show that the difference between the different maturities in terms of liquidity has gradually and drastically narrowed. This is in line with Agbodji (2022) who, considering a larger sample of EU banks over a longer period (2010-2019), finds that the difference between the maturities becomes increasingly insignificant. More importantly, they find that the most liquid maturity in 2015, 2017, 2018 and 2019 is not the 5-year one, but rather the 1-year maturity (in 2015 and 2017) and the 6-month maturity (in 2018 and 2019).

When considering the US sample (Panel B), overall, the difference between the different maturities of CDS has also narrowed from 2008 to 2017 but not as markedly as in Panel A. The most liquid maturity remains the 5-year whatever the period considered (the average absolute bid-ask spreads of the 5-year maturity is the lowest compared to that of the other maturities). This result is then confirmed at the individual level[26] (when we analyze the absolute bid-ask spreads bank by bank).

Overall, the descriptive analysis shows that if two decades ago the 5-year maturity CDS contracts are by far the most liquid, this is no longer the case since the difference between the maturities in terms of liquidity has considerably decreased over time. Moreover, they disappear in recent years, at least when considering the European CDS market (Agbodji, 2022). We also come to the same conclusions when analyzing the absolute bid-ask spreads of indexes (Panel A and Panel B of Appendix 2.B).

[26] The results of this analysis are too large to be added to the article. However, they are available here: https://1drv.ms/x/s!Ag2o5eNTgsLzwlPngGC6hdoNRdVo?e=rJAOxc

Table 2.2: Summary statistics of the absolute Bid-Ask spreads (CDS liquidity proxy).

In this table, we provide the summary statistics of the absolute bid-ask spreads, for all CDS maturities, and at the level of each year of our study period. Panel A applies to the EU sample (period from 2009 to 2016) while Panel B applies to the US sample (period from 2009 to 2017). In each Panel, **N** is the number of observations. **Mean** (**SD**) is the average (standard deviation). **BAS_Ratio** corresponds to the Mean BAS of a maturity divided by that of the 5-Year maturity. This will allow us to compare the liquidity of the different maturities with each other. A BAS Ratio equal to one means that the maturity is as liquid as the 5-year maturity. When higher (lower) than one, this means that the maturity is less (more) liquid than the 5-year maturity.

Panel A: Summary statistics of the absolute Bid-Ask spreads in Europe.

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
2009	6-Month	7390	34,19	39,11	21,35	2,20
	1-Year	10412	38,56	44,82	25,00	2,48
	2-Year	10454	29,07	30,90	19,00	1,87
	3-Year	10925	22,04	21,89	14,74	1,42
	4-Year	10149	18,47	17,41	12,00	1,19
	5-Year	10925	15,54	14,51	10,00	1,00
	7-Year	10410	13,97	13,26	9,00	0,90
	10-Year	10925	12,44	11,26	8,38	0,80
	All	81590	22,52	27,73	13,53	

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
2010	6-Month	12397	36,92	50,20	17,63	2,36
	1-Year	11930	32,80	43,97	15,80	2,09
	2-Year	11930	26,24	31,96	14,02	1,67
	3-Year	12452	20,68	24,14	12,03	1,32
	4-Year	11669	18,15	19,33	11,01	1,16
	5-Year	12452	15,67	16,53	10,00	1,00
	7-Year	11930	15,11	15,74	9,31	0,96
	10-Year	12452	14,51	15,34	9,98	0,93
	All	97212	22,50	31,05	11,66	

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
2011	6-Month	12161	82,54	141,11	30,66	2,21
	1-Year	11641	78,57	138,74	27,87	2,10
	2-Year	11641	58,74	93,97	24,08	1,57
	3-Year	12161	45,86	72,70	19,90	1,23
	4-Year	11457	42,12	69,38	18,33	1,13
	5-Year	12163	37,33	67,84	15,02	1,00
	7-Year	11641	37,16	72,86	14,57	1,00
	10-Year	12161	37,30	83,00	13,65	1,00
	All	95026	52,43	98,36	19,28	

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
2012	6-Month	12030	105,97	216,54	37,47	2,36
	1-Year	11508	90,86	168,01	35,12	2,02
	2-Year	11508	67,32	107,69	30,73	1,50
	3-Year	12030	55,83	95,86	24,65	1,24
	4-Year	11508	51,09	87,59	21,92	1,14
	5-Year	12030	44,89	84,20	20,00	1,00
	7-Year	11508	48,06	91,38	20,00	1,07
	10-Year	12030	49,99	100,69	20,37	1,11
	All	94152	64,25	128,99	25,35	

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
2013	6-Month	12412	49,79	101,77	17,88	1,90
	1-Year	11890	51,34	100,54	19,85	1,96
	2-Year	11890	41,54	66,35	20,00	1,58
	3-Year	12412	35,13	52,88	20,00	1,34
	4-Year	11884	32,21	44,38	19,99	1,23
	5-Year	12412	26,23	38,47	16,53	1,00
	7-Year	11890	27,15	33,53	18,63	1,03
	10-Year	12412	26,10	32,07	18,36	1,00
	All	97202	36,15	65,16	19,26	

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
2014	6-Month	13145	22,92	39,35	10,53	1,40
	1-Year	12623	23,71	35,78	11,33	1,45
	2-Year	12623	22,21	24,77	13,23	1,36
	3-Year	13145	20,46	20,95	13,30	1,25
	4-Year	12623	18,94	18,04	11,42	1,16
	5-Year	13145	16,33	17,26	10,00	1,00
	7-Year	12623	19,54	16,96	13,29	1,20
	10-Year	13145	19,33	16,09	14,29	1,18
	All	103072	20,42	25,23	11,59	

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
2015	6-Month	13311	73,51	371,18	12,56	0,87
	1-Year	12975	69,82	308,11	12,02	0,83
	2-Year	13174	85,89	369,97	13,46	1,02
	3-Year	13299	96,18	447,27	13,32	1,14
	4-Year	13185	86,69	412,88	10,46	1,02
	5-Year	13311	84,58	422,60	10,00	1,00
	7-Year	13173	127,15	858,00	12,00	1,50
	10-Year	13311	102,62	538,33	13,79	1,21
	All	105739	90,83	493,37	12,00	

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
2016	6-Month	13311	72,59	188,23	14,87	1,05
	1-Year	13050	71,86	189,93	14,28	1,04
	2-Year	13311	86,19	282,74	14,74	1,25
	3-Year	13311	80,72	242,54	13,93	1,17
	4-Year	13311	73,38	223,25	13,39	1,06
	5-Year	13311	68,93	210,70	10,33	1,00
	7-Year	13311	63,45	179,09	15,46	0,92
	10-Year	13311	71,07	222,94	16,63	1,03
	All	106227	73,53	219,90	14,67	

Panel B: Summary statistics of the absolute Bid-Ask spreads in the US.

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
2009	6-Month	1747	53,22	82,30	28,87	4,05
	1-Year	2349	46,91	56,30	29,31	3,57
	2-Year	2349	32,12	33,00	20,83	2,44
	3-Year	2349	25,04	24,20	20,00	1,90
	4-Year	2349	19,68	18,28	15,00	1,50
	5-Year	2349	13,16	12,84	10,00	1,00
	7-Year	2349	17,90	13,40	15,00	1,36
	10-Year	2349	17,63	12,40	15,88	1,34
	All	18190	27,38	39,47	20,00	

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
2010	6-Month	2349	18,63	11,79	16,86	2,88
	1-Year	2525	15,77	7,14	15,00	2,44
	2-Year	2525	12,97	5,96	10,00	2,00
	3-Year	2525	11,71	4,75	10,00	1,81
	4-Year	2525	10,83	3,56	10,00	1,67
	5-Year	2525	6,47	3,13	5,00	1,00
	7-Year	2525	10,58	4,00	10,00	1,64
	10-Year	2525	10,62	4,09	10,00	1,64
	All	20024	12,14	6,97	10,00	

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
2011	6-Month	2461	26,47	30,16	16,95	3,07
	1-Year	2600	22,97	24,15	14,92	2,66
	2-Year	2600	18,19	15,62	11,21	2,11
	3-Year	2600	16,02	11,62	10,87	1,86
	4-Year	2600	14,16	9,07	10,00	1,64
	5-Year	2600	8,63	6,39	5,45	1,00
	7-Year	2600	12,65	8,06	9,57	1,47
	10-Year	2600	12,73	7,97	9,82	1,47
	All	20661	16,41	17,05	10,00	

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
2012	6-Month	2803	23,21	18,67	20,00	2,71
	1-Year	2803	23,04	15,33	20,00	2,69
	2-Year	2803	20,05	10,55	16,63	2,34
	3-Year	2803	16,89	7,74	15,00	1,97
	4-Year	2803	13,99	5,51	13,25	1,63
	5-Year	2803	8,57	3,89	8,29	1,00
	7-Year	2803	15,35	5,76	15,00	1,79
	10-Year	2803	17,73	6,42	17,70	2,07
	All	22424	17,36	11,41	15,00	

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
2013	6-Month	3131	13,91	10,42	10,00	2,05
	1-Year	3131	14,46	9,91	11,69	2,13
	2-Year	3131	13,58	8,38	10,00	2,00
	3-Year	3131	12,29	7,75	10,00	1,81
	4-Year	3131	11,23	5,18	10,00	1,65
	5-Year	3131	6,79	3,63	5,00	1,00
	7-Year	3131	14,25	9,40	10,00	2,10
	10-Year	3131	15,65	9,34	10,94	2,30
	All	25048	12,77	8,70	10,00	

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
2014	6-Month	3132	10,90	9,08	8,32	2,12
	1-Year	3132	10,26	8,59	6,75	2,00
	2-Year	3132	9,31	7,45	5,66	1,81
	3-Year	3132	8,17	5,54	5,67	1,59
	4-Year	3132	7,86	4,36	5,45	1,53
	5-Year	3132	5,14	2,86	4,00	1,00
	7-Year	3132	9,73	5,82	9,33	1,89
	10-Year	3132	10,51	6,38	10,00	2,04
	All	25056	8,99	6,79	5,81	

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
2015	6-Month	3132	12,30	15,01	5,80	2,31
	1-Year	3132	10,37	10,86	5,00	1,94
	2-Year	3132	9,63	10,14	5,00	1,81
	3-Year	3132	8,86	8,97	5,00	1,66
	4-Year	3132	8,11	7,49	5,00	1,52
	5-Year	3132	5,33	3,09	4,59	1,00
	7-Year	3132	10,57	10,33	5,31	1,98
	10-Year	3132	11,85	13,00	6,60	2,22
	All	25056	9,63	10,62	5,00	

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
2016	6-Month	3132	16,68	19,28	8,94	2,17
	1-Year	3132	15,77	14,85	9,63	2,05
	2-Year	3132	13,33	12,90	7,93	1,74
	3-Year	3132	12,47	12,07	7,37	1,62
	4-Year	3132	11,31	12,22	5,75	1,47
	5-Year	3132	7,68	5,68	5,00	1,00
	7-Year	3132	15,36	19,66	7,04	2,00
	10-Year	3132	20,64	28,85	10,00	2,69
	All	25056	14,15	17,36	7,96	

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
2017	6-Month	3120	11,93	11,02	7,93	1,63
	1-Year	3120	12,91	8,96	9,32	1,76
	2-Year	3120	11,95	8,03	8,88	1,63
	3-Year	3120	11,29	7,69	8,25	1,54
	4-Year	3120	10,54	7,98	7,14	1,44
	5-Year	3120	7,33	5,25	4,71	1,00
	7-Year	3120	13,11	10,14	10,00	1,79
	10-Year	3120	18,59	16,76	13,30	2,54
	All	24960	12,21	10,43	8,95	

Source: Authors' calculation.

2.3.3.2. Summary Statistics

In this subsection, we present the summary statistics of the data we used to perform our event studies (i.e. the MID spreads of CDS and CDX). Panel A (Panel B) of Table 2.3 provides the summary statistics of the tested banks' CDS MID spreads in the US (Europe), at the aggregate level[27]. In Appendix 2.C, we provide the summary statistics of the two indexes' MID spreads: the *Markit CDX North America Investment Grade Index* (Panel A) and the *Markit iTraxx Europe Investment Grade index* (Panel B).

Table 2.3: Summary statistics of the CDS MID spreads of tested banks.

The summary statistics below are computed at the aggregate level (considering all tested banks), over the period **from 2008 to 2017 in the US** and **from 2009 to 2016 in Europe**. In each Panel, **N** is the number of observations. **Mean** (**SD**) is the average (standard deviation). **Min** is the Minimum while **Max** is the Maximum. **pX** corresponds to the Xth percentile.

One can notice the existence of very high MID spreads (Max) at the level of each maturity. These record levels of CDS MID spreads (that represent less than 0,5% of our database) were reached by a small number of banks during the recent crises that shook the US and Europe (the financial crisis of 2007–2008 and the Great Recession that followed, the European debt crisis of 2010–2013, the Greek government-debt crisis of 2009–2018).

Panel A: Summary statistics of the tested banks' CDS MID spreads in the US (at the aggregate level).

Country	Maturity	N	Mean	SD	Min	Max	p1	p5	p50	p95	p99
US	6-Month	25008	65,0169	144,215	2,79	8305,8	6	8,03	27,54	242,51	525,91
	1-Year	28319	116,286	349,519	0,4	10427,2	7,53	11	39,115	426,335	1177,9
	2-Year	28319	125,719	315,97	0,5	10273,1	11,765	17,5	51,45	412,085	1144,3
	3-Year	28319	134,817	291,533	0,6	9868,1	16,425	25	66,435	404,69	1071,5
	4-Year	28319	143,749	274,128	0,8	9652	21,98	33,5	79,715	398,7	1041
	5-Year	28319	153,779	261,125	1	9526,8	28,415	42,27	93,895	395,05	1000,5
	7-Year	28319	163,082	239,573	3,7	9273	42,095	56,095	109,9	381,6	912,7
	10-Year	28317	169,873	220,369	7,4	8978,7	51,85	64,01	122	375,47	846,9
	All	223239	135,064	271,675	0,4	10427,2	8,57	16	79,58	385,885	956,1

Source: Authors' calculation.

Panel B: Summary statistics of the tested banks' CDS MID spreads in Europe (at the aggregate level).

Country	Maturity	N	Mean	SD	Min	Max	p1	p5	p50	p95	p99
Europe	6-Month	96157	233,044	617,463	2,325	21501,7	6,02	12,42	74,21	900,185	3205,12
	1-Year	96029	243,174	550,367	4,15	18240,8	9,64	16,765	85,945	975,35	2984,86
	2-Year	96531	245,068	460,199	8,285	13264,2	18,2	27,78	104,93	952,69	2363,28
	3-Year	99735	253,717	467,019	12,965	10976,7	26,34	37,515	119,115	966,72	2180,81
	4-Year	95786	267,709	422,24	22,525	9597,92	40,98	50,68	139,353	967,01	2033,88
	5-Year	99749	266,896	391,605	26,5	10066,1	47,84	58	150	933,48	1888,24
	7-Year	96486	273,43	405,347	32,95	10449,7	57,12	68,86	163	896,14	1676,42
	10-Year	99747	274,29	358,839	39,19	10492,5	61,685	75,14	173,14	836,26	1626,07
	All	780220	257,272	465,656	2,325	21501,7	13,01	26,16	129,41	923,285	2179,71

Source: Authors' calculation.

[27] We also analyze the same summary statistics but year by year, at the level of each maturity. The tables are too large to be added and are available here: https://1drv.ms/x/s!Ag2o5eNTgsLzwlJzxI0EvzpFwZZi?e=btE4Xe

2.4. Empirical Results

In this paper, using the CDS spreads of all maturities, we examine the CDS market reaction to the disclosure of regulatory stress test results. In other words, we examine the market response by taking into account all CDS maturities available (not only the 5-year maturity) in order to highlight possible differences in reactions depending on the maturity considered. We present the results in Tables 2.4 and 2.5, and in Figures 2.1 and 2.2. More precisely, Table 2.4 presents the estimates of the CDS market response to the disclosure of EU-wide stress test results, at the level of all maturities. Panel A applies to the 2010 CEBS stress test while Panel B, C and D apply respectively to the 2011, 2014 and 2016 EBA stress tests. Figure 2.1 then presents graphically these different estimates, test by test. Table 2.5 provides the estimates of the CDS market response to the disclosure of US stress test results, for all CDS maturities[28]. Panel A applies to the 2009 Supervisory Capital Assessment Program (SCAP) while Panel B, C, D, E and F apply respectively to the 2013, 2014, 2015, 2016 and 2017 Dodd-Frank Act Stress Tests (DFAST). All estimates in this table are represented graphically in Figure 2.2.

[28] For the 2009 SCAP (Panel A), we could not estimate the market response using the 6-month and the 7-year maturities because of missing data.

<u>Table 2.4</u>*:* The impact of the disclosure of European stress test results.

Maturity	Number of banks	CAARs	SD (CARs)	Min (CARs)	Max (CARs)	Patell p-value (1)	BMP p-value (2)	KP p-value (3)	GenSign p-value (4)	GRANK p-value (5)
Panel A: The 2010 CEBS Stress test										
6-Month	41	-10,38%	8,5%	-37,6%	4,4%	+++	+++	***	+++	***
1-Year	40	-10,46%	8,6%	-37,6%	4,3%	+++	+++	**	+++	**
2-Year	39	-9,17%	7,0%	-29,0%	4,6%	+++	+++	**	+++	**
3-Year	41	-7,88%	5,2%	-19,1%	4,9%	+++	+++	**	+++	**
4-Year	38	-6,88%	5,9%	-18,2%	12,1%	+++	+++		+++	**
5-Year	41	-7,00%	6,3%	-18,7%	15,6%	+++	+++		+++	**
7-Year	39	-7,74%	5,3%	-18,7%	4,3%	+++	+++	*	+++	**
10-Year	41	-8,11%	5,5%	-19,6%	4,2%	+++	+++	*	+++	**
Panel B: The 2011 EBA Stress test										
6-Month	39	2,49%	6,1%	-10,7%	19,0%	+++	+++		**	
1-Year	38	2,63%	6,1%	-10,4%	18,9%	+++	+++		**	
2-Year	37	2,48%	6,3%	-11,4%	18,6%	+++	+++		**	
3-Year	39	2,16%	6,2%	-10,6%	18,5%	+++	+++		*	
4-Year	36	2,46%	5,7%	-10,6%	17,0%	+++	+++		*	
5-Year	39	2,13%	5,5%	-10,2%	17,1%	+++	+++		**	
7-Year	37	1,90%	5,8%	-11,3%	16,1%	+++	+++		*	
10-Year	39	1,59%	6,9%	-15,4%	18,0%	+++	***			
Panel C: The 2014 EBA Stress test										
6-Month	49	-0,03%	12,3%	-26,5%	32,0%	**	**		**	
1-Year	47	-0,57%	11,4%	-25,4%	30,2%	**	**		**	
2-Year	48	-0,59%	10,4%	-24,5%	26,4%	***	**			
3-Year	50	-1,38%	9,5%	-24,5%	20,7%	+++	**		*	
4-Year	48	-2,62%	7,4%	-21,6%	6,5%	+++	+++		**	
5-Year	50	-3,42%	7,3%	-24,1%	6,2%	+++	+++		***	
7-Year	48	-1,35%	8,3%	-30,2%	21,8%	+++	***			
10-Year	50	-3,21%	8,4%	-28,1%	17,3%	+++	+++	*	+++	**
Panel D: The 2016 EBA Stress test										
6-Month	33	-4,82%	5,9%	-22,4%	4,1%	+++	+++	*	+++	**
1-Year	33	-4,51%	5,8%	-21,8%	4,2%	+++	+++	*	+++	**
2-Year	33	-3,59%	4,5%	-15,4%	4,4%	+++	+++	*	+++	**
3-Year	33	-3,36%	4,1%	-15,0%	4,6%	+++	+++	*	+++	**
4-Year	33	-2,67%	3,9%	-12,2%	5,4%	+++	+++		+++	**
5-Year	33	-2,76%	3,1%	-11,7%	3,4%	+++	+++	*	+++	**
7-Year	33	-2,04%	3,1%	-10,9%	3,6%	+++	+++		***	**
10-Year	33	-2,24%	3,1%	-10,3%	3,6%	+++	+++	*	***	**

<u>Source</u>: Authors' calculation.

<u>Notes</u>: This Table presents the estimates of the CDS market response to the disclosure of EU-wide stress test results, in the time period from 2009 to 2017 and at the level of all CDS maturities. Panel A applies to the 2010 CEBS stress test while Panel B, C and D apply respectively to the 2011, 2014 and 2016 EBA stress tests. For each panel (so for each stress test), we have eight different rows corresponding to the eight different estimates (according to the eight different CDS maturities) of the CDS market response to the disclosure of the corresponding stress test results. Considering each row, the first column corresponds to the CDS *Maturity* used to estimate the market response while the second column reports the *Number of banks* in the sample used to estimate the market response. This latter

(CAARs) which is the average of individual banks' reactions (CARs) is reported in the third column whereas the fourth one provides an indication of the dispersion of these individual reactions around the CAARs (standard deviation of CARs). The next two columns show respectively the minimum individual reaction (Min CARs) and the maximum individual reaction (Max CARs). *CAARs* refers to the Cumulative Average Abnormal (CDS) Returns computed employing an event study methodology (on a *three-day* event window including the event date and the two following days (t, t+1, t+2), with a *120-trading day* estimation window covering the period [t-130 ; t-11]). To establish its statistical validity, we use three parametric tests and two non-parametric tests. The columns (1), (2) and (3) report the results of the parametric tests (respectively the *Patell* test, the *Boehmer-Musumeci-Poulsen* test and the *Kolari-Pynnonen* test) while the columns (4) and (5) provide the results of the non-parametric tests (respectively the *Generalized Sign* test and the *Generalized Rank* test). *, **, ***, +++ indicate statistical significance respectively at 10%, 5%, 1% and 0,1% levels.

Table 2.5: The impact of the disclosure of US stress test results.

Maturity	Number of banks	CAARs	SD (CARs)	Min (CARs)	Max (CARs)	Patell p-value (1)	BMP p-value (2)	KP p-value (3)	GenSign p-value (4)	GRANK p-value (5)
Panel A: The 2009 SCAP										
6-Month	–	–	–	–	–	–	–	–	–	–
1-Year	9	-13,41%	7,7%	-23,3%	2,2%	+++	+++		**	**
2-Year	9	-13,46%	6,6%	-22,3%	0,6%	+++	+++	*	**	**
3-Year	9	-13,21%	4,8%	-20,1%	-5,1%	+++	+++	**	***	**
4-Year	9	-13,51%	4,5%	-20,6%	-6,3%	+++	+++	***	***	**
5-Year	9	-12,97%	5,4%	-24,9%	-7,3%	+++	+++	*	***	**
7-Year	–	–	–	–	–	–	–	–	–	–
10-Year	9	-16,49%	8,2%	-31,0%	-3,4%	+++	+++	***	***	**
Panel B: The 2013 DFA Stress test										
6-Month	11	-0,10%	15,9%	-44,6%	11,3%					
1-Year	11	3,31%	7,5%	-7,7%	12,6%					
2-Year	11	2,32%	3,3%	-2,1%	7,5%				**	
3-Year	11	1,81%	2,8%	-1,2%	6,4%					
4-Year	11	0,21%	2,1%	-4,3%	3,1%					
5-Year	11	0,63%	2,0%	-3,3%	3,0%				**	
7-Year	11	0,11%	3,2%	-7,1%	5,2%					
10-Year	11	0,08%	3,4%	-3,8%	7,5%					
Panel C: The 2014 DFA Stress test										
6-Month	11	-11,72%	14,0%	-37,9%	0,5%	**	***		**	**
1-Year	11	-10,01%	13,4%	-33,7%	2,5%	+++	***			
2-Year	11	-6,22%	6,2%	-15,3%	1,6%	***	***			*
3-Year	11	-4,87%	3,7%	-12,7%	0,1%	***	+++	*	***	**
4-Year	11	-3,19%	3,5%	-11,7%	0,1%	**	***		***	
5-Year	11	-3,05%	2,8%	-9,2%	0,0%	+++	***		+++	
7-Year	11	-1,47%	2,7%	-7,3%	1,8%					
10-Year	11	-1,04%	1,3%	-2,9%	0,6%				**	

Panel D: The 2015 DFA Stress test										
6-Month	11	4,48%	10,0%	-16,7%	19,6%		*		*	
1-Year	11	-0,60%	6,3%	-16,6%	7,0%					
2-Year	11	1,84%	6,1%	-9,9%	11,2%					
3-Year	11	0,54%	3,5%	-3,3%	8,5%					
4-Year	11	1,02%	2,8%	-2,3%	7,4%					
5-Year	11	0,97%	1,2%	-1,0%	2,9%				**	
7-Year	11	1,67%	2,0%	-1,0%	5,7%				*	
10-Year	11	1,16%	1,5%	-1,2%	3,2%					
Panel E: The 2016 DFA Stress test										
6-Month	11	18,43%	9,8%	0,8%	29,8%	+++	+++	***	+++	**
1-Year	11	14,49%	7,0%	-0,6%	22,6%	+++	+++	***	***	***
2-Year	11	13,98%	4,9%	2,3%	19,5%	+++	+++	+++	+++	***
3-Year	11	14,02%	4,4%	4,7%	19,0%	+++	+++	+++	+++	***
4-Year	11	12,15%	3,5%	7,7%	16,9%	+++	+++	+++	+++	***
5-Year	11	10,38%	3,7%	2,2%	15,6%	+++	+++	**	+++	**
7-Year	11	9,05%	2,9%	2,6%	14,5%	+++	+++	***	***	***
10-Year	11	9,67%	2,6%	4,6%	14,3%	+++	+++	+++	***	***
Panel F: The 2017 DFA Stress test										
6-Month	12	-1,95%	6,2%	-8,9%	11,1%	**				
1-Year	12	-2,62%	6,5%	-11,3%	10,5%	**				
2-Year	12	-3,24%	5,5%	-10,7%	7,7%	***	*		*	
3-Year	12	-3,36%	5,2%	-15,0%	3,7%	***	*		*	
4-Year	12	-3,80%	4,1%	-13,9%	2,7%	+++	***		***	**
5-Year	12	-2,69%	3,4%	-11,2%	2,5%	+++	**		***	
7-Year	12	-3,80%	5,8%	-21,0%	1,9%	+++	***		**	*
10-Year	12	-3,93%	6,2%	-22,3%	1,5%	+++	***		*	**

Source: Authors' calculation.

Notes: This Table presents the estimates of the CDS market response to the disclosure of US stress test results, in the time period from 2009 to 2017 and at the level of all CDS maturities. Panel A applies to the 2009 Supervisory Capital Assessment Program (SCAP) while Panel B, C, D, E and F apply respectively to the 2013, 2014, 2015, 2016 and 2017 Dodd-Frank Act stress tests (DFAST). For each panel (so for each stress test), we have eight different rows corresponding to the eight different estimates (according to the eight different CDS maturities) of the CDS market response to the disclosure of the corresponding stress test results. Considering each row, the first column corresponds to the CDS *Maturity* used to estimate the market response while the second column reports the *Number of banks* in the sample used to estimate the market response. This latter (CAARs) which is the average of individual banks' reactions (CARs) is reported in the third column whereas the fourth one provides an indication of the dispersion of these individual reactions around the CAARs (standard deviation of CARs). The next two columns show respectively the minimum individual reaction (Min CARs) and the maximum individual reaction (Max CARs). *CAARs* refers to the Cumulative Average Abnormal (CDS) Returns computed employing an event study methodology (on a *three-day* event window including the event date and the two following days (t, t+1, t+2), with a *120-trading day* estimation window covering the period [t-130 ; t-11]). To establish its statistical validity, we use three parametric tests and two non-parametric tests. The columns (1), (2) and (3) report the results of the parametric tests (respectively the *Patell* test, the *Boehmer-Musumeci-Poulsen* test and the *Kolari-Pynnonen* test) while the columns (4) and (5) provide the results of the non-parametric tests (respectively the *Generalized Sign* test and the *Generalized Rank* test). *, **, ***, +++ indicate statistical significance respectively at 10%, 5%, 1% and 0,1% levels.

For each panel of Tables 2.4 and 2.5 (so for each stress test), we have eight different rows corresponding to the eight different estimates of the CDS market response to the disclosure of the corresponding stress test results. Considering each row, the first column corresponds to the CDS Maturity used to estimate the market response while the second column reports the Number of banks in the sample used to estimate the market response. This latter (CAARs) which is the average of individual banks' reactions (CARs) is reported in the third column whereas the fourth one provides an indication of the dispersion of these individual reactions around the CAARs (standard deviation of CARs). The next two columns show respectively the minimum individual reaction (Min CARs) and the maximum individual reaction (Max CARs). Then, to establish the statistical validity of our estimated CAARs, we use three parametric tests and two non-parametric tests. Columns (1), (2) and (3) report the results of the parametric tests (respectively the *Patell* test, the *Boehmer-Musumeci-Poulsen* test and the *Kolari-Pynnonen* test) while the columns (4) and (5) provide the results of the non-parametric tests (respectively the *Generalized Sign* test and the *Generalized Rank* test).

2.4.1. Is the Market Response the Same for All CDS Maturities?

We observe that, for each panel of Table 2.4, all CAARs (whatever the CDS maturity used) have the same sign. In other words, when we consider each EU-wide stress test, all the eight CAARs estimated have the same sign. They are either negative and significant (tests of 2010, 2014 and 2016) or positive and significant (test of 2011); the statistical significance of CAARs in panel A (2010 CEBS test) and Panel D (2016 EBA test) being particularly strong. When considering US SCAP and DFA stress tests (Table 2.5), we come to the same conclusions. Indeed, the eight CAARs estimated for each of the panel A, C, E and F have the same sign. They are either negative and significant (Panels A, C and F) or positive and significant (Panel E), whatever the maturity considered. As we can see, these four Panels show a strong statistical significance, especially the Panel A (2009 SCAP) and the Panel E (2016 DFAST). However, we observe a serious lack of statistical significance for the set of CAARs of the 2013 (Panel B) and 2015 (Panel D) DFA stress tests. That's why we do not consider them.

In view of the foregoing, we support that the nature of the CDS market response to the release of a regulatory stress test results is the same from one maturity to another. More precisely, for a given stress test, the CDS market will not react positively on one maturity (significant negative CAARs) and negatively on another one (significant positive CAARs). According to our empirical results, the nature of the reaction is the same for all CDS maturities: either a positive reaction or a negative reaction.

However, is the extent of the reaction also the same from one maturity to another?

Our empirical investigations suggest that this is not the case. For a given stress test, even if the nature of the response following the disclosure is the same for all CDS maturities, its extent (magnitude) clearly differs from one maturity to another in most cases. Indeed, for each panel presented in Tables 2.4 and 2.5, we observe that the different CAARs' values differ substantially from one maturity to another, with the notable exception of the 2009 US SCAP[29]. Moreover, we observe that for a given stress test, the CAARs (in absolute value) appear to be often higher on short-term maturities than on 4-year maturity or more. In most cases, the lower the maturity of the CDS, the stronger the market reaction i.e. the higher the CAARs in absolute value[30]. This is the case when we consider the 2014 and 2016 US DFA stress tests, and all European stress tests except that of 2014. For the latter and the 2017 US stress test, the CAARs' value also differs from one maturity to another but in these cases (especially the 2014 European test), the lower the maturity of the CDS, the weaker the market reaction i.e. the lower the CAARs in absolute value.

Overall, these results evidence that the impact of the disclosure varies from one maturity to another since the CAARs estimated using different CDS maturities differ substantially. Our results therefore suggest that following the disclosure of a given

[29] Our results highlight a unique and singular situation concerning the market reaction following the US SCAP results' disclosure (which was the first disclosure of a regulatory stress test results in the world). Indeed, we observe that the different CAARs are very close to each other. In other words, participating banks experience on aggregate very significant and negative abnormal CDS returns at the level of all maturities, but there are almost no differences between these abnormal returns. By cons, for each of the 2014, 2016 and 2017 DFA stress tests, our results (reported respectively in the Panels C, E and F of Table 2.5) show that the CAARs vary substantially from one maturity to another; what goes in the same direction as the results that we obtained by analyzing European tests.

[30] Graphically, this results by an ascending curve below the x-axis (in case of *positive reaction*) or a downward curve above the x-axis (in case of *negative reaction*).

stress test results, with the new, reliable and relevant information provided, the CDS market reacts (responds) differently depending on the maturity of the CDS, so on the horizon. It may react strongly on one maturity (very high CAARs in absolute value) and weakly on another one (very low CAARs in absolute value). In most cases, it seems to react more strongly on short-term maturities (whatever the nature of the reaction) since CAARs are higher in absolute value. Nevertheless, our investigations show the opposite in other cases.

2.4.2. What Determines the Difference in the CDS Market Response?

The empirical findings presented in the previous section offer a number of interesting implications that we discuss in what follows.

The spread of CDS is a relatively pure pricing of the default risk of the underlying entity (Zhang *et al.*, 2009). Moreover, according to Ball and Cuny (2020), the term structure of a bank CDS spreads is a function of two components of investors' uncertainty about the bank's asset value. First, the uncertainty from immediately available information that are imprecise (Duffie and Lando, 2001) and second, the uncertainty created by the anticipated arrival of unpredictable economic shocks that will affect the bank's asset value throughout the future (Black and Scholes 1973; Merton 1976; Leland 1994). For authors, these two components of uncertainty offer different implications for the assessed probability of default, and therefore the magnitude of CDS spreads, at different horizons.

In the light of the above, our results suggest that prior to the test, market participants overvalue or undervalue the default risk of tested banks whether in the short-term or in the long-term period, not only because of the degree of noise or imprecision in the information set available to them on the tested banks' situation, but also because of the uncertainty about the occurrence of unpredictable economic shocks. This strongly explains their significant reactions to the disclosure of new information (Holthausen and Verrecchia, 1988; Kim and Verrecchia, 1991; Hautsch and Hess, 2007). Hence, with the new, reliable and relevant information provided, market participants reassess the default risk of participating banks over different horizons and adjusts accordingly their corresponding spreads of CDS, at the level of the different maturities. This adjustment can take the form of an *upward correction* (i.e. an increase in the CDS spread) in the event of undervaluation of the default risk, or a *downward correction* (i.e. a decrease in the CDS spread) in the event of overvaluation of the default risk. But, according to our results, for a given stress test, the nature of the correction is the same for all CDS maturities: either an *upward correction* for all maturities, or a *downward correction* for all maturities.

However, our results also evidence that for a given stress test, market participants correct (adjust) differently the spreads of CDS of tested banks depending on the maturity considered, so on the horizon. For the same test, they can make substantial adjustments to the CDS spread of one maturity, and minor adjustments to that of another maturity. To better understand this, we must further consider the two components of investors' uncertainty about the bank's financial strength.

According to Ball and Cuny (2020), at short term, since the amount of time that investors are exposed to possible future economic shocks is small, the uncertainty about the bank situation is primarily driven by the first component (i.e. the imprecision of immediately available information) while the influence of the second component (i.e. uncertainty about the occurrence of shocks) is relatively negligible. As a consequence, the first component of uncertainty has a stronger influence on short-term CDS spreads while the influence of the second one is relatively weak or insignificant. And the more the CDS maturity increases, the more the relative influence of the second component increases since investors are increasingly exposed to unexpected possible economic shocks. For example, a market participant who wants to trade a short-term maturity CDS contract (example of 6-month or 1-year contracts) will be more concerned about uncertainties about the situation of the bank (the imperfection of available information) than uncertainties about the ability of the latter to cope with macroeconomic shocks that may occur in the future. And the more the maturity will increase, the more his interest in the resilience of the bank to unexpected macroeconomic shocks will increase.

However, the information produced during the stress test and provided with the results' disclosure attempt precisely to reduce these two components of the market participants' uncertainty. In fact, the information produced can also be split in two components. In the first one, there are new, detailed, reliable and valuable information on the exact situation of each tested bank. This aims to reduce the uncertainty resulting from the imperfection of the information available, whose influence is stronger on short-term CDS spreads. In the second component, information produced by regulators highlight and show whether the participating banks have sufficient financial strength to absorb losses and to remain solvent and strongly capitalized, even in a distressed economic environment. This aims to reduce the uncertainty regarding the arrival of unpredictable economic shocks, whose relative influence is stronger on long-term CDS spreads.

In view of the above, our results suggest that short-term CDS spreads are primarily impacted by the reliable and valuable new information on tested bank's situation, while the impact of the new information on bank resilience is relatively weak since the amount of time that investors are exposed to possible unexpected economic shocks is small. As the CDS maturity increases, the relative influence of this information also increases since investors are increasingly exposed to unpredictable future economic shocks. Hence, long-term CDS spreads are more influenced by the new information on banks' ability to absorb losses and to remain strongly capitalized, even in a difficult economic environment. We therefore support that information provided following the disclosure of stress test results are useful for all maturities of CDS, not just for the 5-year maturity. More importantly, we support that information provided impact differently spreads of CDS depending on the maturity of the CDS contract. Accordingly, evaluating the informative value of a stress testing exercise using only the 5-year maturity CDS spreads is not sufficient because results will be partial and incomplete insofar as they do not take into account the fact that spreads are impacted by the two components of the information provided, whose influence differ from one CDS maturity to another. This, in turn, can lead to misinterpretations of the informative content of stress test results, and therefore, an incorrect appreciation of the effectiveness and informative value of regulatory stress tests.

In summary, to better understand and fully appreciate the market response, and to better evaluate the informative content of the disclosed stress test results, we recommend to use not only the 5-year maturity CDS spreads (and/or another long-term maturity), but also the CDS spreads of at least one of the short-term maturities (6-month, 1-year, 2-year and 3-year maturities).

2.4.3. Robustness Checks

To check the reliability of our findings, we carry out a whole battery of robustness tests by employing a number of different specifications regarding the estimation window (used to estimate the market model parameters), the event window, the CDS market (CDX) index, the sample and data used etc... The results are presented in this section.

2.4.3.1. Alternative Estimation and Event Windows

To assess the robustness of our results, we first consider two alternative estimation windows (in place of the 120-trading days window used). More precisely, we consider a shorter estimation window of 84-trading days (following Covi and Ambrosini, 2016) and a longer one of 200-trading days. Overall, the results from these two alternative estimation windows[31] are very similar to that of the 120-trading days window (almost the same), thus strongly confirming our findings and conclusions.

In addition, we also run robustness checks regarding the event windows. More precisely, we consider four alternative event windows ([-2, +2]; [-3, +3]; [0, +1] and [0, +3]) and the results obtained[32] are in line with our main findings.

2.4.3.2. Alternative CDS Market Index

Here, we further investigate the robustness of our results by using a financial CDX index. Indeed, to estimate the CDS market reaction to stress tests, we employ benchmark (multisectoral) Indexes following the literature and since these latter are the most traded. Also, these indexes have the highest number of traded maturities (3, 5, 7 and 10-year maturities). As robustness check, we therefore employ a financial sector CDS index. To our best knowledge, the only financial CDX that exist is the

[31] The estimation of the market response when we employ these two alternative estimation windows are available here: https://1drv.ms/x/s!Ag2o5eNTgsLzwlXC89xN0O_cv4jI?e=Naz881

[32] The estimation of the market response when we employ these four alternative event windows are available here: https://1drv.ms/x/s!Ag2o5eNTgsLzwlQpFeHnvUUeaD8E?e=wHkCo1

Markit iTraxx Europe Senior Financial index which is composed of 25 financial entities from the *Markit iTraxx Europe index* referencing senior debt[33]. We then collect daily data from Bloomberg (CMA New York source) but not for all maturities. Indeed, only two maturities are traded by this index (5 and 10-year maturities). We therefore derive the 7-year maturity data (daily CDX spreads) from a linear interpolation of the 5 and 10-year maturities data. For the remaining unavailable maturities (6-month, 1, 2, 3 and 4-year), we assigned them the spreads of the nearest available maturity to perform our investigations (so the spreads of the 5Y maturity). Whatever the estimation window considered, our results[34] and conclusions are robust. In other words, the use of a financial CDX does not really affect our main findings and conclusions.

2.4.3.3. Estimation of the Market Reaction After Deleting Extreme Spreads.

Analyzing the summary statistics of the tested banks' CDS MID spreads (Table 2.3), one can notice the existence of very high spreads at the level of each maturity, in the US as in Europe[35]. These record levels of CDS spreads were reached by a small number of banks during the recent crises that shook the US and Europe (the financial crisis of 2007–2008 and the Great Recession that followed, the European debt crisis of 2010–2013, the Greek government-debt crisis of 2009–2018). To make sure that our results and conclusions are not driven by these spreads, as robustness check, we re-estimate the market reaction after "*Trimming*" or "*Winsorizing*" our data. "*Trimming*" implies the removal of extreme values (beyond the 98th percentile for our estimation) while "*Winsorizing*" implies to replace extreme values by a certain percentile (the 98th percentile for our estimation).

The new results obtained[36] are very similar to our findings. This leads us to conclude that our results are robust and are not due to these high CDS spreads.

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[33] In other words, the *Markit iTraxx Europe Senior Financial index* comprises 25 equally weighted credit default swaps on investment grade European financial entities.

[34] The estimation of the market response when we employ a financial CDX are available here: https://1drv.ms/x/s!Ag2o5eNTgsLzwllLD7d5YNZn1uHu?e=Wa31X3

[35] Whether we consider the US sample or the European sample, CDS spreads are highly skewed at the level of all maturities (right-skewed distribution).

[36] The results are available here : https://1drv.ms/x/s!Ag2o5eNTgsLzwlqa8nF4l4ZTMuil?e=MaxLYQ

2.4.3.4. Estimation of the Market Reaction with A Balanced Sample of Banks.

Considering each of the EU-wide stress tests of 2010, 2011 and 2014, one can notice that the number of banks in the sample used to estimate the market response differs very slightly from one maturity to another because of missing data. To ensure that our findings (at the level of the 3 tests) are not due to these differences, we re-estimate the market reaction by removing banks that have missing data on one or more maturities, so that we have the same sample of banks from one maturity to another. The results show that there are almost no differences between our findings and the new estimations[37]. In other words, estimate the market response with the same sample of banks from one maturity to another does not really change our results and conclusions in the vast majority of cases.

Overall, robustness tests demonstrate that our results are not due to particular specifications, extreme values or unbalanced sample of banks. They remain unchanged regardless of the alternative specifications employed or the corrections made. This strongly confirms our findings and conclusions.

2.5. Conclusion

In this paper, we were interested to know whether the only use of the 5-year maturity CDS spreads in the examination of the market response to stress tests is sufficient. In other terms, does the sole use of the 5-year maturity entirely reflect the market response? Does it reveal all the informative value of a stress testing exercise? Since the latter measures the tested banks' risk at different horizons, we logically suspect a difference in its impact (i.e. in the CDS market response) depending on the horizon (i.e. on the maturity of the CDS contract). Furthermore, as suggest by Agbodji (2022), each of the different information provided should impact differently the tested banks' spreads of CDS depending on the maturity, thus suggesting the impossibility for the 5-year maturity alone to reflect the entire market response and the stress tests' informative value. We therefore investigate whether the response of market

[37] The estimation of the market response when we employ the same sample of banks from one maturity to another are available here: https://1drv.ms/x/s!Ag2o5eNTgsLzwlvvhlwU5KAkSK2a?e=Jvzqgz

participants to the disclosure differs from one maturity to another, using all maturities of CDS and considering ten regulatory stress tests carried out in Europe and in the US, in the time period from 2009 to 2017.

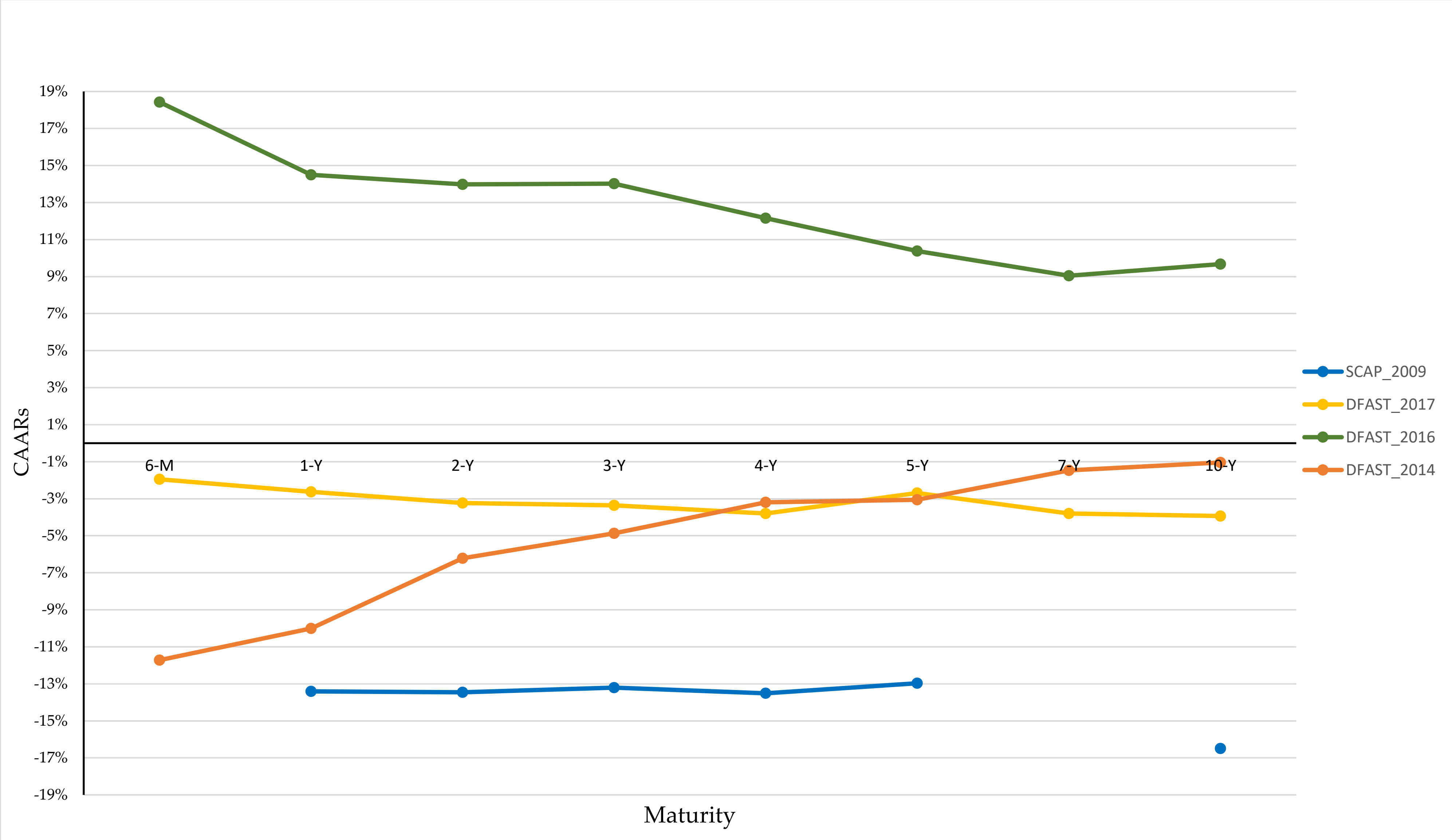
Our results show that, for a given stress test, the impact of the disclosure on the CDS market varies from one maturity to another since the CAARs estimated using different CDS maturities differ substantially. The CDS market may react strongly on one maturity and weakly on another one. This suggests that with the new and relevant information provided, the CDS market reassesses the default risk of participating banks over different horizons and adjusts accordingly their corresponding spreads of CDS, at the level of the different maturities. This adjustment differs however, depending on the CDS maturity considered, so on the horizon. We explain this difference in the adjustment by the fact that the disclosure not only improves the quality and the quantity of information available on these banks' situation (first component), but it also provides valuable information on their resilience to possible future economic shocks (second component). The longer the maturity of the CDS, the weaker the relative influence of the first component on spreads and the greater the relative influence of the second component since investors are increasingly exposed to economic shocks. Hence, analyzing the CDS market response using only the 5-year maturity contracts is not sufficient because results will be partial and incomplete. Short-term CDS maturities matter.

Figures

Figure 2.1: The impact of the disclosure of European stress test results

Source: Authors' calculation.

Figure 2.2: The impact of the disclosure of US stress test results.



Source: Authors' calculation.

Appendix 2

Appendix 2.A: List of tested banks included in our final sample, test by test.

Considering a given stress test column, × indicates tested banks with available data on tradable credit default swap (so banks with available CDS spread returns). Hence, it indicates banks that we consider to examine the impacts of the test.

Panel A: List of banks included in our final US sample

Bank Name	Bank Country	2009 SCAP	2013 DFA test	2014 DFA test	2015 DFA test	2016 DFA test	2017 DFA test
Ally Financial Inc	U.S.	×	×	×	×	×	×
American Express Co	U.S.	×	×	×	×	×	×
Bank of America Corp	U.S.	×	×	×	×	×	×
Capital One Financial Corp	U.S.	×	×	×	×	×	×
CIT Group Inc	U.S.						×
Citigroup Inc	U.S.	×	×	×	×	×	×
JPMorgan Chase & Co	U.S.	×	×	×	×	×	×
Morgan Stanley	U.S.	×	×	×	×	×	×
The Goldman Sachs Group Inc	U.S.	×	×	×	×	×	×
The PNC Financial Services Group Inc	U.S.		×	×	×	×	×
US Bancorp	U.S.		×	×	×	×	×
Wells Fargo & Co	U.S.	×	×	×	×	×	×
Total number of US banks included in our study sample		**9**	**11**	**11**	**11**	**11**	**12**
Total number of US banks covered by the stress test		**19**	**18**	**30**	**31**	**33**	**34**
The share of the total assets of banks included in our study sample compared to that of banks covered by the stress test		**80,94%**	**89,54%**	**81,16%**	**80,15%**	**77,53%**	**77,37%**

Sources: U.S. Federal Reserve (FED) and Authors' calculation.
Notes: All the above companies are **banks**, with the exception of the first 2 (Ally Financial Inc. and American Express Co) which belongs to the "**Diversified Financial Services"** industry. To calculate the shares, we collect annual data on Total Assets from Bankscope Fitch IBCA, for all US banks covered by our considered stress tests. Detailed information are available here: https://1drv.ms/x/s!Ag2o5eNTgsLzwlxXec34XU3nmg5-?e=jjz7Af

Panel B: List of tested banks included in our final European sample

Bank_Name	**Bank Country**	**2010 CEBS test**	**2011 EBA test**	**2014 EBA test**	**2016 EBA test**
ABN AMRO Bank NV	NETHERLANDS			×	
Allied Irish Banks PLC	IRELAND	×		×	×
Alpha Bank AE	GREECE	×	×	×	
Banca Monte dei Paschi di Siena SpA	ITALY	×	×	×	×
Banca Popolare di Milano Scarl	ITALY			×	
Banco Bilbao Vizcaya Argentaria SA	SPAIN	×	×	×	×
Banco BPI SA	PORTUGAL	×	×	×	
Banco Comercial Portugues SA	PORTUGAL	×	×	×	
Banco de Sabadell SA	SPAIN	×	×	×	×
Banco Popolare SC	ITALY	×	×	×	×
Banco Popular Espanol SA	SPAIN	×	×	×	×
Banco Santander SA	SPAIN	×	×	×	×
Bank of Ireland	IRELAND	×	×	×	×
Bankinter SA	SPAIN	×	×	×	
Barclays Bank PLC	BRITAIN	×	×	×	×
BAWAG PSK Bank fuer Arbeit und Wirtschaft und OP AG	AUSTRIA			×	
Bayerische Landesbank	GERMANY	×	×	×	×
BNP Paribas SA	FRANCE	×	×	×	×
Caixa Geral de Depositos SA	PORTUGAL	×	×	×	
Caja de Ahorros del Mediterraneo	SPAIN	×	×		
Commerzbank AG	GERMANY	×	×	×	×
Cooperatieve Rabobank UA	NETHERLANDS	×	×		
Credit Agricole SA	FRANCE	×	×	×	×
Danske Bank A/S	DENMARK	×	×	×	×
Deutsche Bank AG	GERMANY	×	×	×	×
DNB Bank ASA	NORWAY		×	×	×
DZ Bank AG Deutsche Zentral-Genossenschaftsbank	GERMANY	×	×	×	
Erste Group Bank AG	AUSTRIA	×	×	×	×
Eurobank Ergasias SA	GREECE			×	
HSBC Bank PLC	BRITAIN	×	×	×	×
HSH Nordbank AG	GERMANY	×	×	×	
IKB Deutsche Industriebank AG	GERMANY			×	
ING Bank NV	NETHERLANDS	×	×	×	×
Intesa Sanpaolo SpA	ITALY	×	×	×	×
KBC Group NV	BELGIUM	×	×	×	×
Landesbank Baden-Wuerttemberg	GERMANY	×	×	×	×
Landesbank Hessen-Thueringen Girozentrale	GERMANY	×		×	×
Lloyds Bank PLC	BRITAIN	×	×	×	×
Mediobanca Banca di Credito Finanziario SpA	ITALY			×	
National Bank of Greece SA	GREECE			×	
Norddeutsche Landesbank Girozentrale	GERMANY			×	×
Nordea Bank AB	SWEDEN	×	×	×	×
Permanent TSB Group Holdings PLC	IRELAND		×	×	

Piraeus Bank SA	GREECE			×	
Raiffeisen Zentralbank Oesterreich AG	AUSTRIA	×		×	
Royal Bank of Scotland PLC/The	BRITAIN	×	×	×	×
Skandinaviska Enskilda Banken AB	SWEDEN	×	×	×	×
Societe Generale SA	FRANCE	×	×	×	×
Svenska Handelsbanken AB	SWEDEN	×	×	×	×
Swedbank AB	SWEDEN	×	×	×	×
UniCredit SpA	ITALY	×	×	×	×
Unione di Banche Italiane SpA	ITALY	×	×	×	×
Total number of EU banks included in our study sample		**41**	**40**	**50**	**33**
Total number of EU banks covered by the stress test		**91**	**90**	**123**	**51**
The share of the total assets of banks included in our study sample compared to that of banks covered by the stress test		**82,25%**	**82,11%**	**78,26%**	**81,73%**

Sources: European Banking Authority (EBA) and Authors' calculation.
Notes: All the above companies are **banks**. To calculate the shares, we collect annual data on Total Assets from Bankscope Fitch IBCA, for all EU banks covered by our considered stress tests. Detailed information are available here: https://1drv.ms/x/s!Ag2o5eNTgsLzwlxXec34XU3nmg5-?e=jjz7Af

Panel C: Different countries in the EU final sample

Country	**Number of banks**
Austria	3
Belgium	1
Britain	4
Denmark	1
France	3
Germany	9
Greece	4
Ireland	3
Italy	7
Netherlands	3
Norway	1
Portugal	3
Spain	6
Sweden	4
Total number of participating banks	**52**

Sources: European Banking Authority (EBA) and Authors' calculation.

Appendix 2.B: Summary statistics of the **absolute Bid-Ask spreads of indexes** (CDS liquidity proxy).

The summary statistics below are computed over the period **from 2008 to 2017 in the US** and **from 2009 to 2016 in Europe**. In each Panel, **N** is the number of observations. **Mean** (**SD**) is the average (standard deviation). **CV** is the Coefficient of variation (also known as relative standard deviation) which is the ratio of the standard deviation to the mean. **Min** is the Minimum while **Max** is the Maximum. **pX** corresponds to the Xth percentile.

Panel A: Summary statistics of the absolute Bid-Ask spreads of the *Markit CDX North America Investment Grade Index*.

Index Name	Index Country	Maturity	N	Mean	SD	CV	Min	Max	p1	p5	p10	p25	p50	p75	p90	p95	p99
Markit CDX North America Investment Grade Index	US	3-Year	2490	1,921578	1,348725	0,70188	0	8	0,33	0,37	0,44	0,53	2	3	3,415	4,46	5,76
		4-Year	2488	1,315215	0,766506	0,58280	0	6,5	0,404999	0,435001	0,470001	0,525002	1,25	1,790001	2,375	2,5	3,375
		5-Year	2602	0,73869	0,503494	0,68160	0	6,97	0,34	0,45	0,48	0,5	0,5	0,89	1,06	2	2,9
		7-Year	1767	1,957731	0,98573	0,50351	0,44	15,27	0,51	0,61	0,9	1,07	2	2,5	3,07	3,53	4,37
		10-Year	2528	1,70481	1,152964	0,67630	0	8,13	0,45	0,5	0,58	1	1,5	2	3,04	4,2	6,12
		All	11875	1,494579	1,09491	0,73259	0	15,27	0,35	0,45	0,5	0,529999	1,14	2	3	3,5	5

Source: Authors' calculation.

Panel B: Summary statistics of the absolute Bid-Ask spreads of the *Markit iTraxx Europe Investment Grade index*.

Index Name	Index Country	Maturity	N	Mean	SD	CV	Min	Max	p1	p5	p10	p25	p50	p75	p90	p95	p99
Markit iTraxx Europe Investment Grade index	Europe	3-Year	2085	1,212782	0,733526	0,60483	0	5,17	0,39	0,47	0,51	0,59	1	1,71	2	2,98	3,29
		4-Year	2082	0,967752	0,452027	0,46709	0	4,169998	0,445	0,499996	0,510002	0,560005	0,879997	1,215	1,5	1,830002	2,300003
		5-Year	2083	0,722357	0,289346	0,40056	0	3,17	0,43	0,5	0,5	0,5	0,66	0,9	1	1	2
		7-Year	2084	1,19844	0,87662	0,73147	0	7,45	0,44	0,44	0,47	0,555	1	1,5	2	2,51	5,42
		10-Year	2083	1,133735	0,729253	0,64323	0	6,36	0,38	0,43	0,44	0,56	1	1,5	2	2,21	4,9
		All	10417	1,047067	0,677581	0,64712	0	7,45	0,400002	0,46	0,494995	0,54	0,94	1,23999	1,96	2,09	3,38

Source: Authors' calculation.

Appendix 2.C: Summary statistics of the **MID spreads of indexes**.

The summary statistics below are computed over the period **from 2008 to 2017 in the US** and **from 2009 to 2016 in Europe**. In each Panel, **N** is the number of observations. **Mean** (**SD**) is the average (standard deviation). **CV** is the Coefficient of variation (also known as relative standard deviation) which is the ratio of the standard deviation to the mean. **Min** is the Minimum while **Max** is the Maximum. **pX** corresponds to the Xth percentile.

Panel A: Summary statistics of the *Markit CDX North America Investment Grade Index'* **MID spreads**.

Index_Name	Index_Country	Maturity	N	Mean	SD	CV	Min	Max	p1	p5	p10	p25	p50	p75	p90	p95	p99
Markit CDX North America Investment Grade Index	US	3-Year	2490	67,47591	46,46569	0,68863	25,41	295,23	26,35	29,3	31,875	37,72	53,3425	77,92	111,4275	186,5	254,03
		4-Year	2488	80,4613	40,77578	0,50678	36,945	281,44	39,545	43,815	46,6025	52,76625	69,58375	90,7575	120,145	183,02	247,13
		5-Year	2602	96,04323	37,73439	0,39289	48,48	279,74	52,6	57,77	61,99	69,25	86,9	108,5	140,35	185,75	237,27
		7-Year	1767	103,2356	17,44471	0,16898	71,49	166,38	74,775	78,93	83,93	89,825	100,205	113,25	129,17	137,655	149,21
		10-Year	2528	122,4445	19,67266	0,16067	85,92	242,52	92,91	99,575	103	109,0875	118,49	130,7175	147,17	157,47	193,16
		All	11875	93,4791	40,14821	0,42949	25,41	295,23	29,25	37,425	46,19	63,78	91,5	114,675	136,64	156,57	231,22

Source: Authors' calculation.

Panel B: Summary statistics of the *Markit iTraxx Europe Investment Grade index'* **MID spreads**.

Index_Name	Index_Country	Maturity	N	Mean	SD	CV	Min	Max	p1	p5	p10	p25	p50	p75	p90	p95	p99
Markit iTraxx Europe Investment Grade index	Europe	3-Year	2085	75,82818	40,48944	0,53396	27,75	238,63	30,17	33,795	37,5	44,625	66,555	91,34	144,34	164,96	199,89
		4-Year	2082	88,52629	37,58626	0,42458	37,935	222,73	42,205	46,57	50,3225	58,605	80,80875	104,8925	156,025	168,545	192,745
		5-Year	2083	101,2772	35,57937	0,35131	47,74	208,37	53	59,1	63,125	72,605	95,68	118,96	162,02	176,13	196,67
		7-Year	2084	116,3301	31,43749	0,27024	64,63	218,6	70,03	78,525	82,92	91,9125	108,7575	136,6175	162,55	182,925	199,97
		10-Year	2083	127,5113	28,9194	0,22680	79,665	224,94	84,25	91,38	96,235	106,29	119,62	147	169,955	187,785	205,68
		Total	10417	101,8923	39,65891	0,38922	27,75	238,63	33,795	43,6475	52,5	71,955	97,685	125,805	159,525	177,67	198,84

Source: Authors' calculation.

CHAPTER 3 | Time horizons, *Baseline* and *Adverse* Scenarios: A New Assessment of the Information Content of Regulatory Banking Stress Tests.*

* This chapter draws from the working paper "Time horizons, Baseline and Adverse Scenario: A New Assessment of the Information Content of Regulatory Banking Stress Tests." co-authored with Dr. Emmanuelle NYS (Université de Limoges, LAPE) and Prof. Alain SAUVIAT (Université de Limoges, LAPE). We thank the members of the "Laboratoire d'Analyse et de Prospective Économiques (LAPE)", especially Dr. Ruth Tacneng for their valuable comments and suggestions which helped to improve this paper.
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3.1. Introduction

A regulatory stress testing exercise is a scenario-based supervision tool used by banking supervisors to assess and analyze the robustness of participating banks, in order to ensure that they have sufficient financial strength to absorb losses and to remain solvent and strongly capitalized, even in a distressed economic environment. Initially considered as a crisis management tool as it was carried out in the aftermath of the Global Financial Crisis in an attempt to restore investors' confidence in the soundness of the banking system, stress tests have continued to be performed during the post-crisis period and are now established as one of the main banking supervision tools. Their objective is to test, individually and as a whole, the resilience of participating banks to different forward-looking macroeconomic scenarios. In general, one can distinguish (i) a *baseline* scenario based on the most recent macroeconomic projections and (ii) an *adverse* scenario built as a "dark" scenario characterized by harmful but plausible financial and economic situations. Both scenarios are designed over three different time horizons (1-year, 2-year and 3-year) and each tested bank's financial strength is assessed at the level of each horizon.

At the end of an exercise, a set of data that reflects the evolution of the financial health of each tested bank throughout the forward-looking scenarios (including data on capitalization, solvency, market risk, credit risk, counterparty risk, liquidity risk, operational risk…) is disclosed in a very detailed way, in addition to various reviewed financial data of tested banks. While there is a large literature on whether market participants take into account these disclosed outcomes in their assessment of banking risks, to our best knowledge, no paper interprets these outcomes according to the specific characteristics of the scenarios implemented. We aim to fill this gap by studying how market participants react to the disclosure of stress tested characteristics of banks, depending on the profiles and time horizons of the scenarios built by supervisors.

Most of the papers which study the informative value of the regulatory stress test find significant reactions from market participants (stock market, CDS market…) following the disclosure, as they highlight significant abnormal movements in the (stock) prices and (CDS or bond) spreads of tested banks around the release date. These results show that stress testing exercises provide new and relevant information to market participants on the tested banks' financial strength, in addition to improving the quality and quantity of information available (among others, Petrella and Resti, 2013; Morgan *et al.*, 2014; Carboni *et al.*, 2017; Flannery *et al.*, 2017; Georgescu *et al.*, 2017; Ahnert *et al.*, 2018; Fernandes *et al.*, 2020 and Agbodji *et al.*, 2021). We aim to go further by studying whether market participants derive new and relevant information from the outcomes of each of the two scenarios implemented during stress testing exercises and, if so, whether this information differs depending on the scenario and the time horizon. In other words, since the *baseline* and the *adverse* forward-looking scenarios are not designed and elaborated in the same way, we consider distinctly the disclosed outcomes of both in order to examine whether each determines the market reaction and whether their informative content is identical or not, taking into account the 1-year, 2-year and 3-year time horizons. For this purpose, this paper studies the determinants of the abnormal movements in the CDS premium of tested banks following the disclosure considering all the different maturities of CDS (from 6-month to 10-year maturity) following Agbodji *et al.* (2021).

We consider Credit Default Swap instead of stocks or bonds because given its characteristics, it is the most appropriate instrument to use. Indeed, since the information provided has different temporalities (as it is provided for each time horizon of each scenario), in order to estimate the reaction of market participants to its disclosure, we should use instruments which also have different temporalities. Agbodji *et al.* (2021) show it well and following the latter, we consider CDS as it has different temporalities (maturities), unlike stocks[38]. Furthermore, stress tests provide to market participants reliable information on the ability of tested banks to absorb losses and to remain strongly solvent, even in a distressed economic environment and over different time horizons. Accordingly, CDS is the most suitable instrument to use as it reflects the market perception of the financial strength of a reference entity (banks), at different horizons. Also, its spread is a relatively pure pricing of default risk

[38] Bonds also have different maturities but the latter are not uniform across firms and vary considerably over time (Han and Zhou, 2015). On the contrary, the maturities of the CDS contracts are strictly standardized (they are the same across banks) and fixed over time. Since our empirical investigations are based on a group of tested banks, this represents a major advantage.

of the underlying entity (Zhang *et al.*, 2009), unlike bond spreads or stock prices. Finally, as shown by Blanco *et al.* (2005), CDS spreads appear to react more accurately and rapidly to new information regarding the underlying reference entity compared to bond spreads, especially in the short run. This represents a key advantage for our study since using an event study methodology, we attempt to capture banks' abnormal performances over a relevant and short window around the disclosure date.

We perform our empirical investigations based on the EU-wide stress testing exercises conducted by the European Banking Authority (EBA) in 2014, 2016 and 2018. We do not consider the remaining European tests (the 2010 and 2011 exercises) because the number of bank-level variables that were stress tested was very limited, especially in 2010. With regard to our sample, out of a total of 133 European banks (from 22 EU countries) that participated in at least one of the three tests, we select listed banks for which data on tradable CDS contracts are available for all the different CDS maturities, resulting in a total of 53 banks. We only study the European case because, for each American stress test, the number of tested banks with available data on tradable CDS does not exceed 10.

Our results evidence that following the disclosure, not only the abnormal movements in the CDS premium differ depending on the maturity of the CDS contract (as expected), but also the stress test outcomes that determine these abnormal movements. In other words, the information that makes market participants react is not the same from one CDS maturity to another, suggesting that the informative content of the disclosed outcomes differs depending on the time horizon. It differs depending on whether one considers the short-term horizon (6-month, 1-year and 2-year) which seems to be the most provided in informational content, or the medium- or long-term horizon. Moreover, only the outcomes from the *baseline* scenario seem to have provided market participants with such informative content. According to our results, market participants seem to have drawn no new and relevant information on tested banks' risks and situation from the *adverse* scenario outcomes, whatever the scenario time horizon considered. Going further, our results also evidence that the change in Common Equity Tier 1 ratio during the test do not influence market participants, unlike the change in several other tested banks' characteristics. This may seem surprising and unanticipated since in the large list of bank characteristics that are tested, it is the principal and the most important as it summarizes most factors captured by stress testing exercises. However, the results of our robustness tests suggest that this may be due to the relative high level of capitalization of tested banks during our study period, compared to the period from 2010 to 2011 where the first stress tests took place. Indeed, after a high wave of recapitalization following the Global Financial Crisis, banks are currently considered to have safety cushions large enough to absorb potential operating losses, thereby ensuring a low risk of insolvency (i.e. bankruptcy). Our results corroborate such an argument as for the 2010 and 2011 exercises, market participants reacted to the disclosure of stress test capital variables.

Our study contributes to the existing literature in the following ways. Firstly, to our best knowledge, this paper is the first to empirically examine whether the two stress test scenarios' outcomes each provides new and relevant information to market participants, and whether or not their informative content is identical considering the different maturities of CDS in the estimation of the market reaction. Hence, it is the first to investigate whether the outcomes that determine the market reaction differ depending on the maturity of the CDS contract. This paper therefore attempts to improve the understanding of whether and how the information released following stress testing exercises determines the reaction of market participants, taking into account the specificities and the different time horizons of each implemented scenario. Hence, we contribute to the existing empirical literature on the informative value of regulatory stress tests (Sahin and Haan, 2016; Flannery *et al.*, 2017; Georgescu *et al.*, 2017; Ahnert *et al.*, 2018; Sahin *et al.*, 2020 and Agbodji *et al.*, 2021). Our findings may have important policy implications for banking supervisors since we shed some light on the precise stress test scenarios and outcomes that influence market participants, depending on the time horizon and the test period (crisis or tranquil period). It may also help researchers to better examine the informative content of stress tests' disclosed outcomes and better understand the market response and the factors driving it. Secondly, EU-wide stress tests are primarily focused on the assessment of the impact of risk drivers on the solvency of banks (EBA Methodological Note, 2016, p.13). However, according to our findings, the change in common equity tier 1 ratio does not always influence market participants and to our best knowledge, this paper is the first to highlight that. This may have some implications for banking supervisors in the design of the methodology and the scenarios of future stress testing exercises. Thirdly, our study shows (once again) the usefulness of regulatory stress testing exercises, even outside crisis or panic periods. There is always new and relevant information that is revealed to market participants, as our results prove. Hence, this paper also contributes to the debate on transparency in banking supervision (Jordan, 2000; Dudley, 2009; GAO, 2010 and Goldstein and Sapra, 2011) since our results show that the disclosure of stress test outcomes can help market participants to better assess and comprehend the risks and the value of tested banks. This, in turn, can help them better discriminate between strong banks and weak banks, which in the end strengthens market discipline (Flannery, 2001).

The rest of our paper is structured as follows. Section 3.2 first provides an overview of the related literature and then presents the research questions investigated. Section 3.3 introduces the sample of banks under consideration and describes the data and empirical approach. Section 3.4 presents our results while some robustness checks are discussed in Section 3.5. Section 3.6 finally concludes.

3.2. Related Literature and Research Question

There is a large empirical literature on the regulatory banking stress tests that have been carried out following the Great Financial Crisis of 2007–2008. Overall, the authors have been interested in their informative value by examining whether or not they provide new and relevant information to participants in the various financial markets.

Petrella and Resti (2013) investigate how the 2011 European stress test affects the stock market. After showing a significant reaction from market participants upon the disclosure of the results, they evidence in a multivariate analysis that this stock market response is primarily and significantly determined by the *adverse* scenario outcomes. Indeed, they show that regressors based on *adverse* stress tested data appear to be highly significant in driving the market reaction (e.g. the change in coverage ratio at the end of the scenario for defaulted exposures and for credit exposures, the increase in the cost of funding…). Their results also suggest that a positive stock market reaction is significantly associated with a higher level of common equity tier 1 ratio prior to the exercise. Georgescu *et al.* (2017) find that new and useful information was provided to the stock and the CDS market participants around the announcement of the key features of the 2014 and 2016 EBA stress tests, and following the results' disclosure. This new information was priced and allows markets to better discriminate between strong banks and weak banks. Indeed, authors show that under the *adverse* scenario, stock prices of banks that lost a large part of their Common Equity Tier 1 ratio (what prove their weakness) performed significantly worse than those of the stronger banks upon the publication of the 2014 test. In 2016, weaker banks experienced significantly higher positive abnormal CDS returns compared to better performing banks. Flannery *et al.* (2017), examining the nine US stress tests performed until 2015, highlight significant reactions from the stock market participants following most of the exercises. By contrast, the participants in the CDS market only react to the 2009 SCAP. They then find that banks with higher leverage have larger abnormal stock returns and larger abnormal trading volumes on disclosure dates, especially tested banks. Moreover, their results indicate that stress testing exercises are more informative about riskier banks in general. Focusing on six US CCAR and four EBA stress tests performed over the 2010–2017 period, Ahnert *et al.* (2018) suggests that stress testing exercises reduce bank opacity by improving the quality and the quantity of information available on tested banks' situation. Hence, they allow markets to better discriminate between strong banks which are rewarded (positive abnormal equity returns and tighter CDS spreads) and weak banks which are sanctioned (significant drops in equity prices and widening CDS spreads). Afterwards, they find that at the release, higher and positive equity market reaction is determined by higher capital buffer, higher asset quality, lower leverage, and a less risky business model. However, their results also show that none of the bank characteristics explain the abnormal (5-year maturity) CDS performance. This may be because authors consider solely the 5-year maturity CDS contract in their investigations. Questioning the relevance of this choice, Agbodji *et al.* (2021) investigate the market response to ten European and US regulatory stress tests, considering the eight different maturities of CDS. Their results show that information provided (after the stress test results' disclosure) is useful for all maturities of CDS, not just for the 5-year maturity. More precisely, they show that this information impacts differently spreads of CDS depending on the maturity considered. This suggests that the pricing by market participants of the information provided differs according to the maturity of the CDS contract, and therefore according to the time horizon. Hence, to fully appreciate and evaluate the market response to a stress testing exercise, authors recommend using not only the 5-year maturity CDS spreads (and/or another long-term maturity), but also the CDS spreads of the short-term maturities (6-month, 1-year, 2-year and 3-year maturities).

In view of this finding, investigating the informative content of the disclosed stress test outcomes (i.e. the information that makes market participants react) considering the different maturities of CDS may provide new insight on the effectiveness of this supervision tool. To perform these empirical investigations, it may more appropriate to consider the EU-wide stress tests conducted by the European Banking Authority (EBA) since 2014. Not only this choice makes it possible to have a sufficient number of tested banks with available data on tradable credit default swaps (for all maturities from 6-month to 10-year), but also, it makes it possible to have a homogeneity of the disclosed outcomes.

EBA stress testing exercises are performed over two distinct forward-looking macroeconomic scenarios: a *baseline* and an *adverse* scenario. Provided by the European Commission, the *baseline* scenario is based on the most recent macroeconomic projections produced by the national central banks, prior to the stress test. On the other hand, we have the *adverse* macro-financial scenario that is the severe scenario. It is designed and built by the Task Force on Stress Testing of the European Systemic Risk Board (ESRB), in close collaboration with the European Central Bank (ECB). It outlines the evolution of key economic and financial variables in a hypothetical severely adverse situation capturing the materialization of relevant risks to which the EU banking system is exposed (ESRB, 2020, p. 1). Each of the two scenarios is designed over three different time horizons (1-year, 2-year and 3-year). Compared to the *baseline* scenario that is entirely based on economic projections, the *adverse* one is built on severe economic and financial shocks that reflects the four systemic risks that are assessed (by the ECB) as representing the most material threats to the stability of the

EU banking sector. In this regard, it is the one that provides reliable information on tested banks' resilience throughout hypothetical extreme (but plausible) crisis periods, compared to the *baseline* scenario. Indeed, by simulating possible economic shocks, it is the one that "really" challenges the capital position and the financial health of EU banks. Previous papers that examined EU-wide stress tests pointed it out and consequently consider the *adverse* scenario outcomes in their empirical investigations, instead of the *baseline* scenario outcomes (among others, Petrella and Resti, 2013). On another side, however, the *baseline* scenario being more plausible as corresponding to the most recent economic forecasts, one can argue that market participants will also be interested in it since it gives them an idea about the possible financial health of tested banks over the next few years. Hence, there are arguments which support the two possibilities. This justifies our choice to consider distinctly the outcomes of both scenarios in order to examine whether each explains the reaction of market participants following the disclosure, and whether their informative content is identical or not. Furthermore, as the pricing by market participants of the information provided differs depending on the maturity of the CDS contract (Agbodji *et al.*, 2021), we also examine whether the stress test outcomes that explain the reaction of market participants vary depending on the maturity of the CDS contract.

3.3. Sample, Methodology, and Data

In this section, we present respectively the sample on which this study is based, the methodology employed and the data used to perform our empirical investigations.

3.3.1. Sample

3.3.1.1. European Stress Tested Banks

The stress testing exercises that we consider for this paper are the 2014, 2016 and 2018 EU-wide stress tests which are the ones that have been conducted by the European Banking Authority since 2014. We do not consider the two exercises performed before 2014 (the 2010 & 2011 stress tests) because the list of banking characteristics that were stress tested was very limited, especially when considering the exercise of 2010. By contrast, from the 2014 exercise, this list is not only more important, but also much more homogeneous. Indeed, the three stress tests have the merit of having in common the majority of the bank characteristics that are stress tested, including the most relevant (described in section 3.3.3.1). This is a major condition for the conduct of our empirical investigations and that is the reason why this study is being conducted from 2014. Consequently, the selection of the banks included in our study sample is made based on the list of banks that have been stress tested during these three exercises.

Initially, there are a total of 133 European banks (from 22 EU countries) that participated in at least one of these three tests. We then remove banks without tradable CDS contracts, resulting in 59 banks. Finally, we take out of the sample banks with no data available over the sample period 2013-2018. In the end, our study sample consists of 53 listed euro area banks for which data on tradable CDS contracts are available (for all the different CDS maturities)[39]. Panel A of Appendix 3.A provides an overview of these banks, test by test. It also provides for each test, the share of the total assets of banks included in our study sample compared to that of banks covered by the stress test. These shares (respectively 78%, 82% and 77% for the 2014, 2016 and 2018 tests) show that banks included in our empirical analysis are representative of the total assets of stress tested banks. Finally, Panel B shows the different countries represented in our final sample with the number of banks per country.

3.3.1.2. Maturity and Liquidity of CDS Contracts

Liquidity in the CDS market reflects the ease with which traders can initiate a contract at an agreeable price (Tang and Yan, 2007). The 5-year maturity CDS contract is generally considered to be, by far, the most liquid segment of the CDS market. This justifies its extensive use by the literature, rather than the other maturities' contracts. However, since this study considers all the different maturities of CDS (not just the maturity of 5-year), before using their spreads, we first analyze their liquidity.

[39] In this study, we consider European stress tests rather than American ones because the number of listed US banks that were tested and for which data on tradable CDS contracts are available (for all the different CDS maturities) does not exceed 10, whatever the test considered.

To measure the liquidity of CDS contracts, following Tang and Yan (2013), Annaert *et al.* (2013) and Samaniego-Medina *et al.* (2016), we use the Bid-Ask spread of the CDS quotes, i.e. the difference between ask and bid quotes. Our choice to use the bid-ask spread is primarily motivated by the fact that it is arguably the most widely used CDS liquidity proxy in finance. Following Samaniego-Medina *et al.* (2016) and Arakelyan and Serrano (2016), we consider the absolute bid-ask spread (rather than the relative one) that we compute on a daily basis. According to Pires *et al.* (2011) and Coro *et al.* (2012), the absolute bid-ask spread is already a proportional measure. As liquidity increases, the size of the bid-ask spread narrows. Considering our sample of 53 listed euro area banks, Appendix 3.B provides the summary statistics of the absolute bid-ask spreads for all CDS maturities, and at the level of each year from 2010 to 2018. Following Agbodji (2022), we calculate a "BAS Ratio" statistic which, at the level of a maturity, is the average bid-ask spread of the latter divided by that of the 5-Year maturity. This will allow us to compare the liquidity of the different maturities with each other. A BAS Ratio equal to one means that the corresponding maturity is as liquid as the 5-year maturity. When higher (lower) than one, this means that the maturity is less (more) liquid than the 5-year maturity.

The summary statistics show that before our study period, i.e. over the period from 2010 to 2013, the higher the CDS maturity, the greater its liquidity in general. Over this period, the most liquid maturities are that of 10-year, 7-year and 5-year since their BAS Ratio is equal to or very close to one, while the remaining maturities' ratio varies on average from 1,70 (in 2010) to 1,60 (in 2013). However, over the study period (from 2014 to 2018), the difference between the CDS maturities in terms of liquidity has considerably narrowed. More precisely, whatever the maturity considered over this period, the BAS Ratio is either equal to one or very close to one, especially from 2015.

Overall, the difference between the maturities of CDS in terms of liquidity has decreased significantly over time until it almost disappears from 2014. Furthermore, the most liquid maturity in 2015, 2017, and 2018 is not the 5-year one, but rather the 1-year maturity (in 2015 and 2017) and the 6-month maturity (in 2018). This is in line with Agbodji (2022) who, considering a larger sample of EU banks over a longer period (2010-2019), comes to the same conclusions. Our descriptive analysis therefore shows that our spreads of CDS are liquid, regardless of the maturity of the CDS contract. Over our study period, the different maturities of CDS are as liquid as the 5-year maturity.

3.3.2. Empirical Investigation Design

In an attempt to find answers to our questions, we carried out several empirical investigations that can be broadly divided into two groups: *(1) an event study* that capture the market reaction to the publication of stress test results and *(2) a multivariate regression analysis* where we extensively examine the drivers of this reaction.

3.3.2.1. Event Study Methodology: Calculating the Cumulative Abnormal Returns (CARs) of CDS Spreads.

Employing an event study methodology (Brown and Warner, 1985; and Campbell, Lo, and MacKinlay, 1997), we capture the market reaction by calculating the Cumulative Abnormal CDS spreads Returns (CAR) over a relevant window around the release date ("*event window*"). More precisely, market participants integrate the information provided into the spreads of CDS of each tested bank (i.e. the information provided are priced). If they deem this information new, significant and relevant, these spreads will experience abnormal movements which are precisely what the CAR measure. Put another way, the CARs estimate the impact of the stress test outcomes' publication on the CDS spreads of each participating bank.

Appendix 3.C describes in detail, the different steps of the event study methodology employed to calculate it. Furthermore, we estimate this market response at the level of all the different maturities of CDS (from 6-month to 10-year maturity) following Agbodji *et al.* (2021).

3.3.2.2 Multivariate Regression Analysis: Explaining the Cumulative Abnormal Returns (CARs) of CDS spreads

Then, to determine whether and how the *baseline* and the *adverse* scenario's outcomes each influences the tested banks' spreads of CDS, considering the different time horizons, we conduct a multivariate regression analysis with the market reaction (CARs) as the dependent variable. We regress the latter on a set of stressed indicators (that quantify the increase or decrease in the leading characteristics of tested banks during the stress tests) and several control variables. The reference model is as follows:

$$\mathrm{CAR}_{i,t}^{\mathrm{M}} = \alpha + \beta . X_{i,t}^{\mathrm{S,H}} + \gamma . Y_{i,t-1} + \lambda . Z_{i,t-1} + \varepsilon_{i,t} \qquad (1)$$

From equation (1), $\mathbf{CAR}_{i,t}^{\mathrm{M}}$ is the market response to the divulgation of the year *t* stress test outcomes about bank *i*, and estimated using the *M*-year maturity CDS spreads. $X_{i,t}^{\mathrm{S,H}}$ corresponds to a set of stressed indicators calculated using the year *t* stress test outcomes about bank *i*, considering the *H*-year horizon of the scenario *S*. $Y_{i,t-1}$ is a battery of observable specific-characteristics of bank *i*, at the most recent year prior to the disclosure of year *t* stress test results. $Z_{i,t-1}$ represents the bank *i*'s market and country characteristics, calculated over the most recent year prior to the disclosure of year *t* stress test results.

3.3.3. Explanatory Variables

In what follow, we describe the explanatory variables of our reference model and their theoretical or empirical relation to CDS spreads. We also present the descriptive statistics of all variables, after analyzing the correlations among regressors.

3.3.3.1. Bank Indicators Built from Stress Test Results

In the databases released following the 2014, 2016 and 2018 EU-wide stress tests, the banks' characteristics assessed are divided into five categories: (i) *Capital*, (ii) *Risk Exposure Amount*, (iii) *Profit & Loss*, (iv) *Credit risk* and (v) *Sovereign*. Even if the content of these categories has been constantly modified (including during the last test in 2018), there are however in each of them several characteristics in common between the three tests. We focus on the most relevant ones based on the literature and on the EU-stress test documents. For each of these banks' characteristics, we compute and consider a stressed indicator which quantify the impact of the stress test scenarios, i.e. the change in the characteristic caused by the simulated scenarios (value at the end of the stressed period minus the value just before the test).

(i) *Capital*

EU stress tests are primarily focused on the assessment of the impact of risk drivers on the solvency of banks (EBA Methodological Note, 2016, p.13). Consequently, we start with the "*Common Equity Tier 1 Ratio*" which is a high-quality capital adequacy ratio. In the large list of tested characteristics, this is the most important since, according to Petrella and Resti (2013), it summarizes most factors captured by the stress testing exercise (initial capital ratio before the test, profitability expectations, credit and market losses, liquidity etc...). This is also the reason why it was used as a trigger by supervisors. A decrease in this ratio following the simulated scenarios should lead to a higher CDS spreads (and vice versa). We therefore expect a negative impact on Cumulated Abnormal CDS spreads Returns.

In this category, we have several other tested characteristics as the Tier 1 Ratio and Capital, the Total Capital Ratio and Capital, the Additional Tier 1 Capital, the Tier 2 Capital, the Retained earnings etc… We select the "*Common Equity Tier 1 Ratio*" following the literature and especially because it is the highest quality capital adequacy ratio, compared to the remaining tested capital ratios[40].

Apart from this ratio, several leading characteristics of tested banks are likely to increase or decrease throughout the stress test periods. We therefore consider the most relevant of them. To keep under control multicollinearity issues, we focus on variables which are not embedded into each other.

(ii) *Risk Exposure Amount / Credit risk*

In the risk coverage approach of EU stress tests, participating banks are required to stress test three common set of risks, namely credit risk (including securitizations), market risk (and counterparty credit risk) and Operational risk including conduct risk (EBA Methodological Note, 2016). We therefore consider as second stress tested characteristic, the change in the "*Total Risk Exposure Amount*" (following Petrella and Resti, 2013). It is the sum of the credit, market, and operational risk exposures and it indicates change in risk profile of asset portfolio of the bank. Following Petrella and

[40] As robustness checks, we perform our estimates using the "*Tier 1 Ratio*" or the "*Total Capital Ratio*" instead of the "*Common Equity Tier 1 Ratio*". As all the results are similar, we report only those of the mainstream model using the "*Common Equity Tier 1 Ratio*". Robustness check estimates are however available from the authors upon request.

Resti (2013) and Flannery *et al.* (2017), we use the ratio of total risk exposure to total assets which provides a measure of riskiness of assets. An increase in this ratio (at the end of the simulated scenarios) indicates a deterioration of overall risk profile of bank assets; this should lead to an increase in CDS spreads, and vice versa. We therefore expect a positive impact on Cumulated Abnormal CDS spreads Returns.

(iii) *Profit & Loss*

In addition to the risks listed above, participating banks are requested to project the effect of the two scenarios on "*Net Interest Income*", on "*Profit & Losses*" and on capital items not covered by other risk types (EBA Methodological Note, 2016, p.13). Hence, we consider the change in the "*Profit & Losses*" and in the "*Net interest Income*" of tested banks. Also, these considerations allow us to take into account in our investigation, the evolution of the participating banks' profitability. As they are in billions of euros, we scaled them by banks' total assets following Petrella and Resti (2013) and Flannery *et al.* (2017). A decrease in these ratios at the end of the simulated scenarios should lead to an increase in CDS spreads. We therefore expect a negative impact on Cumulated Abnormal CDS spreads Returns.

Finally, we consider the "*Accumulated other comprehensive income*" which corresponds to unrealized profits or losses, that we also scaled by banks' total assets. Since they are unrealized (unlike the "*Profit & Losses*" and the "*Net interest Income*"), it is delicate to predict the direction of its impact.

3.3.3.2. Control Variables at the Bank Level

To control for specific characteristics of tested banks, we insert several regressors in our model following the literature.

(i) *Leverage*

The leverage captures bank indebtedness and risk appetite. Too much debt relative to equity can result in a bank failure. Indeed, according to Merton's approach, higher leverage indicates a shorter distance to the default barrier and a higher probability of default (Galil *et al.*, 2014). Furthermore, Ericsson *et al.* (2009), Hasan *et al.* (2014) and Drago *et al.* (2017) among others evidence that it is an important determinant of CDS spreads. To control for it, we use the "ratio of liabilities to the sum of liabilities and equity" following Drago *et al.* (2017), among others. The higher this ratio, the higher the CDS spreads (Drago *et al.*, 2017).

(ii) *Asset quality*

Asset quality is the quality of banks' investments, loans and other assets that could affect its financial condition. Hasan *et al.* (2014) and Drago *et al.* (2017) highlight that it is significantly associated with bank CDS spreads, even when controlling for structural model variables. More precisely, Banks with higher asset quality should have lower probability of default and therefore lower CDS spreads. To proxy for it, we follow among others Drago *et al.* (2017) by using the "ratio of non-performing loans to total assets". The lower the proxy, the higher the asset quality (so the lower the CDS spreads).

(iii) *Management quality*

Management quality refers to the ability of the bank to correctly identify, manage, and control the risks specific to its activities. As a proxy for management quality, following Hasan *et al.* (2014), we use the "cost efficiency ratio", which is the ratio of operating expenses to total revenues. This ratio is positively and significantly related to bank CDS spreads as shown by Hasan *et al.* (2014).

(iv) *Sensitivity to market risk*

It reflects the degree to which changes in interest rates can adversely affect a bank's earnings or capital. To proxy for it, we use the cost of funds (i.e. the ratio of interest expense to total liabilities). According to Hasan *et al.* (2014), banks with higher cost of funds are more sensitive to changes in interest rates and therefore are more vulnerable to changes in market conditions. Moreover, they show that banks with high cost of funds have higher CDS spreads.

(v) *Size*

According to Drago *et al.* (2017), bank size can capture the ability of the bank to diversify risk through economies of scope, and market participants may deem large banks too big to fail. They evidence that bank size is one of the key factors explaining CDS spreads and the higher the bank size, the lower the spreads of CDS. We therefore consider it and use the natural logarithm of bank total assets to proxy for it following the literature.

(vi) *Funding stability*

It is the ratio of deposits to total liabilities. Since retail deposits are a relatively stable source of funding, the higher this ratio, the lower the spreads of CDS and Drago *et al.* (2017) show it. We therefore control for it.

(vii) *Liquidity*

Liquidity is a measure of the cash and other assets banks have available to quickly pay bills and meet short-term business and financial obligations (Federal Reserve). According to Corò *et al.* (2013), firm-specific liquidity factors are critical determinants of CDS spread variations. To control for it, we use the ratio of net loans to deposits and short-term funding following Kosmidou (2008) and Naceur and Kandil (2009). The higher the value of the ratio, the lower the bank liquidity. Hence, this ratio is positively related to bank CDS spreads.

3.3.3.3. Macroeconomic Control Variables

Since our sample includes 14 countries, we also add controls for the specific market and country characteristics of tested banks. Several papers show that CDS spreads are affected by business climate and economic conditions. Consequently, we use the following macroeconomic variables to control for the variation in business and economic conditions over time.

(viii) *Risk-free interest rate*

Ericsson *et al.* (2009) and Hasan *et al.* (2014) evidence that the risk-free rate is a major determinant of CDS spreads as interest rates are positively related to economic growth and negatively related to default likelihood. They highlight a negative relationship between the risk-free rate and CDS spreads. We therefore control for it and as proxy, the 10-year government bond yield is used following Ericsson *et al.* (2009), Hasan *et al.* (2014) and Samaniego-Medina *et al.* (2016).

(ix) *Stock market returns*

A higher stock market returns suggest an improved economic environment (Zhang *et al.*, 2009) and is therefore associated with a reduction in CDS spreads. More precisely, a significant negative impact of market return on CDS spread is evidenced by Samaniego-Medina *et al.* (2016) and Drago *et al.* (2017). To control for it, we employ country-specific stock market indexes.

(x) *Stock market volatility*

The market volatility captures the uncertainty that surrounds economic prospects, and a greater market volatility implies a higher probability of default (Corò *et al.*,2013). Hasan *et al.* (2014) and Samaniego-Medina *et al.* (2016) show that stock market volatility is a significant determinant of bank CDS spreads. They show its significant negative impact on CDS spread. Hence, we take it into account and calculate it as the historical standard deviation of bank's market daily returns over the most recent year prior to the disclosure.

Table 3.1 summarizes the above explanatory variables, the expected direction of their impact (expected sign) and the data sources. Bivariate correlations of all these variables appear separately for *baseline* and *adverse* samples in Table 3.2. More precisely, in this table, we present below the diagonal the correlations among regressors for the *baseline* sample (i.e. when we consider the stressed indicators based solely on the *baseline* scenario outcomes). Above the diagonal, we present the correlations for the *adverse* sample. We compute these correlation coefficients considering the 2-year horizon stress test outcomes[41]. As we can see, the correlations among regressors are very weak in the vast majority of cases. All of them are lower than 0.6 and only 8 correlations (out of 210) are higher than 0.5, i.e. 3.8% of the correlation matrix. This suggests that multicollinearity is unlikely to be a problem in our regressions. However, we still check by carrying out a multicollinearity diagnostic. We conduct a Variance Inflation Factors (VIFs) analysis (Liao and Valliant, 2012; Miles, 2014) whose results are reported in Table 3.3. As we can see, whatever the scenario or the time horizon considered, the

[41] The released stress test data are estimated over 3 different time horizons (1-year, 2-year and 3-year). Since the correlation tables are very similar from one horizon to another, we choose to present only the 2-year time horizon one. However, the 1-year and 3-year time horizon correlation tables are available in the Appendix 3.D.

VIFs are all below 2,08 (it varies from 1,83 to 2,07) thus confirming that the potential issues of multicollinearity are kept under control.

3.3.3.4. Summary Statistics

First, we provide in Table 3.4 the descriptive statistics of the market reaction (the dependent variable) over all the different CDS maturities. Then, Table 3.5 presents the descriptive statistics of stressed indicators (that are based on stress test outcomes). Panel A, B and C applies respectively to the 1-year, 2-year and 3-year scenario time horizon. Finally, we provide in Table 3.6 the summary statistics of control variables, over the period from 2013 to 2018.

3.4. Empirical Results

The estimates of our reference model (equation 1) are reported in tables 3.7, 3.8 and 3.9 which present our findings respectively for the 1-year, 2-year and 3-year scenario time horizon. Following Petersen (2009) suggestions and Hasan *et al.* (2014), we use bank fixed effects to account for unobserved time-invariant bank characteristics and to improve the efficiency of our estimates[42]. In each of the tables 3.7, 3.8 and 3.9, we have two distinct series of regressions: the *Baseline* scenario series and the *Adverse* scenario series. They differ only in the stress test outcomes used to compute the stressed indicators. For the series of regressions of the *baseline* scenario (*adverse* scenario), the stressed indicators are based solely on the *baseline* scenario outcomes (*adverse* scenario outcomes).

[42] After controlling for bank fixed effects, the adjusted R-squared of our model increases substantially. Considering the 1-year time horizon, with bank fixed effects, our model fit increases on average by 159% for the *baseline* regression series and 71% for the *adverse* series. Considering now the 2-year time horizon (3-year time horizon), it increases on average by 107% (74%) for the *baseline* regression series and 39% (20%) for the *adverse* series. It therefore exists some unobserved time-invariant bank characteristics that have important explanatory power for the market reactions to stress test results, whatever the maturity or the time horizon.

Table 3.7: Determinants of the market reaction to the disclosure of 1-year time horizon stress test results.

Market reaction	CAR [-1 ; 2]															
Horizons	1-year Scenario Time Horizon															
Scenarios	**Baseline**								**Adverse**							
Maturity	6-Month	1-Year	2-Year	3-Year	4-Year	5-Year	7-Year	10-Year	6-Month	1-Year	2-Year	3-Year	4-Year	5-Year	7-Year	10-Year
Stressed Indicators																
ΔCET1 Ratio	1.432	2.238	1.773	1.347	0.279	-0.426	-0.947	-0.661	2.233	1.970	2.155	1.633	-0.389	-1.075	0.643	-0.108
	(2.570)	(2.618)	(2.683)	(2.143)	(1.811)	(1.424)	(1.423)	(1.397)	(2.062)	(2.162)	(2.002)	(1.879)	(1.373)	(1.236)	(1.220)	(1.472)
ΔTotal Risk	4.020***	4.017***	3.704***	3.112***	3.131***	1.991**	2.390**	2.403**	1.090	0.820	0.504	0.337	-0.285	-0.729	-0.341	-0.444
	(1.028)	(1.052)	(1.146)	(1.057)	(0.953)	(0.976)	(0.962)	(1.070)	(1.053)	(1.093)	(0.987)	(0.912)	(0.797)	(0.897)	(0.678)	(0.711)
ΔP&L	-11.72***	-10.67**	-9.280**	-6.297	0.591	3.273	-0.585	0.398	-5.594	-5.722	-5.427	-4.211	-0.848	0.821	-1.245	0.112
	(4.248)	(4.195)	(4.225)	(4.099)	(2.671)	(2.739)	(3.809)	(4.237)	(3.475)	(3.464)	(3.453)	(3.053)	(2.796)	(2.908)	(3.136)	(2.940)
ΔNet Int Inc	-16.00**	-22.60***	-24.09***	-24.05***	-18.41***	-12.45	-8.592	-14.05**	-9.282	-16.99*	-18.48**	-18.17**	-12.55*	-10.82	0.340	-6.051
	(6.491)	(6.626)	(5.651)	(5.519)	(5.855)	(8.630)	(5.838)	(5.304)	(9.292)	(9.366)	(8.571)	(8.410)	(7.286)	(7.888)	(7.689)	(7.438)
ΔAccumul Inc	13.67	13.52	16.33	20.46	9.172	8.968	17.79	17.16	-1.295	1.647	4.943	5.624	-2.889	-4.132	0.638	0.890
	(12.92)	(13.58)	(14.41)	(14.55)	(10.25)	(9.979)	(14.66)	(14.36)	(10.78)	(10.57)	(9.783)	(8.892)	(5.171)	(4.268)	(7.259)	(7.763)
Control Variables																
Leverage	2.235	3.146**	2.976*	1.741	2.050	0.979	1.786	1.557	2.629	3.883**	3.587*	2.801**	2.377*	1.615	1.785	1.910
	(1.453)	(1.452)	(1.587)	(1.275)	(1.388)	(1.300)	(1.266)	(1.161)	(2.007)	(1.738)	(1.796)	(1.388)	(1.348)	(1.303)	(1.497)	(1.246)
Managmt Quality	0.00684	0.00485	0.0159	0.0384	-0.0259	-0.0536	-0.118	-0.106	-0.107	-0.127	-0.0874	-0.0522	-0.101	-0.108	-0.135	-0.158
	(0.196)	(0.197)	(0.201)	(0.166)	(0.134)	(0.139)	(0.103)	(0.122)	(0.184)	(0.209)	(0.209)	(0.202)	(0.133)	(0.140)	(0.113)	(0.140)
Size	-0.0903	-0.00651	0.0400	0.0589	-0.0485	-0.132**	-0.0575	-0.0353	-0.110	-0.0436	-0.0255	0.000361	-0.0433	-0.114	-0.0902	-0.0607
	(0.106)	(0.0966)	(0.118)	(0.114)	(0.0489)	(0.0561)	(0.100)	(0.114)	(0.152)	(0.133)	(0.136)	(0.120)	(0.0661)	(0.0682)	(0.0885)	(0.103)
Funding Stability	-0.563	-0.365	-0.211	-0.201	0.196	0.0639	-0.0755	-0.157	-0.448	-0.364	-0.367	-0.344	-0.0140	-0.146	-0.227	-0.347
	(0.398)	(0.381)	(0.361)	(0.337)	(0.217)	(0.207)	(0.299)	(0.316)	(0.487)	(0.449)	(0.424)	(0.381)	(0.240)	(0.213)	(0.349)	(0.330)
Asset Quality	-0.867	-0.588	-0.674	-0.634	-0.851	-0.977*	-1.015*	-0.971*	-0.984	-0.809	-0.749	-0.678	-1.125**	-1.261**	-0.809	-1.030*
	(0.554)	(0.559)	(0.522)	(0.521)	(0.516)	(0.567)	(0.605)	(0.502)	(0.777)	(0.759)	(0.741)	(0.702)	(0.560)	(0.539)	(0.741)	(0.576)
Sensitivity Mkt Risk	-4.984	-2.783	-2.570	-2.993	-1.561	-2.320	-2.558	-3.443	-4.920	-2.182	-2.217	-2.238	-0.218	-0.785	-2.143	-2.694
	(5.923)	(4.451)	(3.828)	(3.637)	(2.517)	(2.399)	(3.659)	(3.456)	(6.502)	(4.976)	(4.310)	(4.050)	(2.354)	(2.063)	(3.780)	(3.692)

Liquidity	-0.0977	-0.0484	-0.0476	-0.0439	-0.0688	-0.101*	-0.0841	-0.0825	-0.0961	-0.0415	-0.0369	-0.0322	-0.0243	-0.0535	-0.0625	-0.0530
	(0.0773)	(0.0686)	(0.0755)	(0.0651)	(0.0493)	(0.0516)	(0.0512)	(0.0550)	(0.0984)	(0.0853)	(0.0919)	(0.0826)	(0.0672)	(0.0611)	(0.0623)	(0.0635)
Risk-Free Rate	3.694	2.165	1.199	-0.123	-1.454	-2.172**	-0.934	-1.137	2.490	1.350	0.449	-0.424	-1.004	-1.385	-1.123	-1.084
	(2.455)	(1.869)	(1.583)	(1.443)	(1.104)	(0.908)	(1.339)	(1.253)	(2.622)	(2.228)	(1.870)	(1.712)	(1.137)	(0.991)	(1.524)	(1.410)
Market Returns	-0.352**	-0.376**	-0.266*	-0.139	0.0717	0.198	0.141	0.0446	-0.222	-0.276**	-0.220	-0.140	0.0974	0.195	0.142	0.0533
	(0.146)	(0.148)	(0.142)	(0.134)	(0.113)	(0.134)	(0.114)	(0.119)	(0.148)	(0.137)	(0.140)	(0.120)	(0.119)	(0.121)	(0.0852)	(0.0918)
Market Volatility	-13.03**	-11.15*	-6.970	-3.207	-1.042	-2.323	0.175	0.0158	-8.032	-7.122	-4.322	-1.596	1.129	-1.260	1.723	1.845
	(5.840)	(5.840)	(6.389)	(5.928)	(3.326)	(3.231)	(4.117)	(4.796)	(7.760)	(7.663)	(7.528)	(6.969)	(4.678)	(3.948)	(3.951)	(4.877)
Constant	0.874	-2.383	-3.584	-2.984	-0.556	2.825*	0.128	-0.200	1.027	-2.040	-2.279	-2.304	-0.951	1.768	1.061	0.224
	(2.998)	(2.880)	(3.626)	(3.172)	(1.822)	(1.598)	(2.712)	(2.975)	(4.763)	(4.223)	(4.668)	(3.765)	(2.310)	(2.032)	(2.695)	(3.001)
Observations	108	106	106	109	107	109	107	109	108	106	106	109	107	109	107	109
R-squared	0.417	0.415	0.393	0.389	0.560	0.534	0.361	0.392	0.245	0.261	0.279	0.290	0.481	0.522	0.259	0.304
Adjusted R-squared	0.322	0.317	0.292	0.291	0.488	0.459	0.256	0.294	0.122	0.137	0.158	0.175	0.395	0.445	0.137	0.191
Number of Banks	53	52	53	53	53	53	53	53	53	52	53	53	53	53	53	53
Prob. > F	0.000	0.000	0	0	0.000	0.000	0.000	0.000	0.022	0.000	0.002	0.000	0	0	0.000	0.000
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustering	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Source: Authors' calculation.

Notes: This table reports the estimates from two distinct series of panel regressions. In each serie, we regress the market reaction (to the divulgation of the 2014, 2016 and 2018 EU-wide stress test results) over a set of five stressed indicators and several control variables. These two series of regressions differ only in the stress test outcomes used to compute the five stressed indicators. For the series of regressions of the *baseline* scenario (*adverse* scenario), the stressed indicators are based solely on the *baseline* scenario outcomes (*adverse* scenario outcomes) estimated over a 1-year time horizon. Then, in each series, we have eight columns which present the estimates of eight distinct regressions that differ from each other only in the maturity used to calculate the market response (i.e. the dependent variable), following Agbodji *et al.* (2021) suggestions. We obtain the market reaction (at the level of all CDS maturities) by estimating the Cumulative Abnormal CDS spread Returns (CAR). We estimate it using an event study methodology over a four-day event window ((-1,+2)), the event being the stress test results' disclosure.

As stressed indicators, we have the **ΔCET1 Ratio** which is the Change in common equity tier 1 ratio caused by the simulated scenarios, scaled by total assets. **ΔTotal Risk** is the Change in total risk exposure amount caused by the simulated scenarios, scaled by total assets. **ΔP&L** is the Change in profit and losses caused by the simulated scenarios, scaled by total assets. **ΔNet Int Inc** is the Change in net interest income caused by the simulated scenarios, scaled by total assets. **ΔAccumul Income** is the Change in accumulated other income caused by the simulated scenarios, scaled by total assets. As control variables, we have the **Leverage** is the Ratio of liabilities to the sum of liabilities and equity. **Managmt Quality** is the Cost efficiency ratio (Ratio of operating expenses to total revenues). **Size** is the Natural logarithm of bank total assets. **Funding Stability** is the Ratio of deposits to total liabilities. **Asset Quality** is the Ratio of non-performing loans to total assets. **Sensitivity Mkt Risk** is the Cost of funds (i.e. Ratio of interest expense to total liabilities). **Liquidity** is the Ratio of net loans to deposits and short-term funding. **Risk-Free Rate** is the Yield on 10-year government bond. **Market Returns** is the Country stock market returns. **Market Volatility** is the Historical standard deviation of daily country market returns. Following Petersen (2009) suggestions and Hasan *et al.* (2014), we use bank fixed effects to account for unobserved time-invariant bank characteristics (that exist and have important explanatory power for the market reactions) and to improve the efficiency of our estimates. Robust standard errors (in parenthesis) are clustered by bank. *, **, *** indicate respectively significance at 10%, 5% and 1% levels.

Table 3.8: Determinants of the market reaction to the disclosure of 2-year time horizon stress test results.

Market reaction	CAR [-1 ; 2]															
Horizons	2-year Scenario Time Horizon															
Scenarios	**Baseline**								**Adverse**							
Maturity	6-Month	1-Year	2-Year	3-Year	4-Year	5-Year	7-Year	10-Year	6-Month	1-Year	2-Year	3-Year	4-Year	5-Year	7-Year	10-Year
Stressed Indicators																
ΔCET1 Ratio	1.281	1.510	0.902	0.697	-0.108	-0.0651	-0.359	-0.179	0.554	0.301	0.366	0.266	-1.392	-1.521*	0.125	-0.183
	(1.693)	(1.653)	(1.604)	(1.355)	(1.026)	(0.924)	(1.083)	(1.028)	(1.748)	(1.797)	(1.744)	(1.618)	(1.044)	(0.882)	(1.051)	(1.162)
ΔTotal Risk	3.416***	3.500***	3.546***	3.111***	2.354***	1.500**	2.162***	2.216**	0.199	-0.0430	0.226	0.241	-0.407	-0.520	-0.268	-0.231
	(0.907)	(0.888)	(0.978)	(0.879)	(0.650)	(0.742)	(0.801)	(0.842)	(0.934)	(1.046)	(0.957)	(0.853)	(0.521)	(0.502)	(0.648)	(0.689)
ΔP&L	-11.20***	-9.953**	-8.743**	-5.254	-0.878	0.678	-0.267	0.976	-8.699**	-6.574	-5.379	-3.297	0.506	1.630	-0.161	1.961
	(4.021)	(4.025)	(4.172)	(3.665)	(2.518)	(2.650)	(3.332)	(3.734)	(4.121)	(4.042)	(4.253)	(3.604)	(2.445)	(2.246)	(3.625)	(3.359)
ΔNet Int Inc	-16.51**	-22.37***	-23.75***	-23.27***	-20.60***	-14.70*	-10.76*	-14.18***	0.374	-6.349	-10.06	-12.16	-12.91**	-13.70**	-0.528	-5.988
	(6.741)	(6.467)	(6.409)	(5.690)	(5.721)	(7.998)	(5.408)	(5.031)	(10.16)	(10.61)	(9.108)	(8.265)	(6.369)	(5.980)	(8.085)	(6.139)
ΔAccumul Inc	25.49*	26.20*	28.57**	30.63**	18.72*	16.29	26.91**	25.67**	-3.960	-0.626	3.317	4.052	-2.124	-2.384	0.957	1.988
	(14.61)	(13.95)	(13.44)	(12.77)	(10.20)	(10.62)	(12.76)	(11.81)	(11.22)	(11.14)	(10.95)	(9.747)	(5.744)	(4.364)	(7.184)	(7.454)
Control Variables																
Leverage	1.833	2.660*	2.428	1.254	1.576	0.698	1.391	0.950	2.302	3.265*	2.960	2.525*	2.721*	2.226*	1.758	1.788
	(1.615)	(1.586)	(1.720)	(1.319)	(1.400)	(1.293)	(1.259)	(1.194)	(1.888)	(1.745)	(2.089)	(1.505)	(1.501)	(1.246)	(1.691)	(1.182)
Managmt Quality	0.0172	0.00323	0.0102	0.0311	-0.0228	-0.0168	-0.101	-0.0905	-0.0910	-0.126	-0.109	-0.0683	-0.131	-0.123	-0.164	-0.176
	(0.189)	(0.187)	(0.190)	(0.158)	(0.115)	(0.127)	(0.106)	(0.115)	(0.165)	(0.174)	(0.177)	(0.170)	(0.115)	(0.124)	(0.113)	(0.124)
Size	-0.00228	0.0843	0.142	0.155*	0.0396	-0.0643	0.0289	0.0499	-0.171	-0.107	-0.0442	0.00295	-0.0194	-0.0789	-0.0981	-0.0506
	(0.120)	(0.102)	(0.100)	(0.0905)	(0.0455)	(0.0615)	(0.0722)	(0.0848)	(0.183)	(0.165)	(0.154)	(0.130)	(0.0594)	(0.0659)	(0.0953)	(0.105)
Funding Stability	-0.533	-0.323	-0.122	-0.107	0.173	0.000701	-0.0460	-0.101	-0.703	-0.541	-0.417	-0.317	0.0719	-0.0400	-0.237	-0.259
	(0.392)	(0.362)	(0.328)	(0.308)	(0.214)	(0.209)	(0.290)	(0.297)	(0.538)	(0.518)	(0.507)	(0.444)	(0.255)	(0.231)	(0.396)	(0.416)
Asset Quality	-0.888	-0.648	-0.680	-0.657	-0.889*	-0.981*	-1.130*	-0.998**	-1.255*	-1.049	-0.920	-0.804	-1.256**	-1.295***	-0.925	-0.997*
	(0.572)	(0.549)	(0.501)	(0.481)	(0.454)	(0.503)	(0.601)	(0.447)	(0.682)	(0.646)	(0.609)	(0.584)	(0.480)	(0.473)	(0.684)	(0.499)
Sensitivity Mkt Risk	-6.081	-3.583	-3.054	-3.223	-0.878	-1.868	-2.818	-3.455	-5.068	-2.324	-2.263	-2.128	0.0530	-0.548	-1.990	-2.631
	(5.833)	(4.126)	(3.661)	(3.477)	(2.654)	(2.787)	(3.590)	(3.478)	(6.214)	(4.968)	(4.536)	(4.145)	(2.278)	(1.937)	(3.835)	(3.812)

Liquidity	-0.0673	-0.0200	-0.0222	-0.0162	-0.0409	-0.0764	-0.0621	-0.0577	-0.109	-0.0546	-0.0470	-0.0351	-0.0182	-0.0435	-0.0660	-0.0537
	(0.0792)	(0.0652)	(0.0665)	(0.0582)	(0.0474)	(0.0507)	(0.0455)	(0.0478)	(0.104)	(0.0957)	(0.0990)	(0.0838)	(0.0634)	(0.0564)	(0.0648)	(0.0656)
Risk-Free Rate	3.170	1.533	0.498	-0.910	-2.082*	-2.357**	-1.553	-1.780	3.535	1.723	0.664	-0.545	-0.936	-1.323*	-1.211	-1.573
	(2.540)	(1.849)	(1.554)	(1.386)	(1.186)	(1.013)	(1.318)	(1.274)	(2.670)	(2.242)	(1.967)	(1.688)	(1.028)	(0.785)	(1.244)	(1.304)
Market Returns	-0.276*	-0.295*	-0.195	-0.0702	0.0910	0.180	0.186*	0.0936	-0.228	-0.233	-0.173	-0.0828	0.147	0.213**	0.163**	0.0921
	(0.156)	(0.152)	(0.138)	(0.121)	(0.104)	(0.128)	(0.106)	(0.104)	(0.153)	(0.149)	(0.145)	(0.117)	(0.0908)	(0.0862)	(0.0810)	(0.0772)
Market Volatility	-9.949	-8.020	-4.015	-0.361	0.650	-1.906	2.358	2.161	-9.343	-7.810	-4.044	-0.628	2.434	-0.457	1.773	2.691
	(5.990)	(6.049)	(5.939)	(5.522)	(3.110)	(2.971)	(3.728)	(4.370)	(8.890)	(8.791)	(8.400)	(7.419)	(4.062)	(3.062)	(4.184)	(4.965)
Constant	-1.160	-4.414	-5.865*	-5.171*	-2.500	1.245	-1.866	-1.986	3.085	0.334	-1.170	-2.142	-1.985	0.171	1.321	0.0311
	(3.406)	(3.089)	(3.391)	(2.785)	(1.920)	(1.869)	(2.270)	(2.484)	(5.666)	(5.094)	(5.668)	(4.397)	(2.471)	(2.104)	(3.412)	(3.235)
Observations	108	106	106	109	107	109	107	109	108	106	106	109	107	109	107	109
R-squared	0.402	0.412	0.408	0.411	0.588	0.552	0.387	0.421	0.241	0.218	0.229	0.252	0.518	0.572	0.254	0.306
Adjusted R-squared	0.304	0.314	0.310	0.316	0.520	0.479	0.286	0.327	0.117	0.0881	0.100	0.131	0.439	0.503	0.131	0.194
Number of Banks	53	52	53	53	53	53	53	53	53	52	53	53	53	53	53	53
Prob. > F	0.000	0.000	0.000	0.000	0	0.000	0.000	0.000	0.076	0.080	0.008	0.000	0	0	0.000	0.000
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustering	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Source: Authors' calculation.

Notes: This table reports the estimates from two distinct series of panel regressions. In each serie, we regress the market reaction (to the divulgation of the 2014, 2016 and 2018 EU-wide stress test results) over a set of five stressed indicators and several control variables. These two series of regressions differ only in the stress test outcomes used to compute the five stressed indicators. For the series of regressions of the *baseline* scenario (*adverse* scenario), the stressed indicators are based solely on the *baseline* scenario outcomes (*adverse* scenario outcomes) estimated over a 2-year time horizon. Then, in each series, we have eight columns which present the estimates of eight distinct regressions that differ from each other only in the maturity used to calculate the market response (i.e. the dependent variable), following Agbodji *et al.* (2021) suggestions. We obtain the market reaction (at the level of all CDS maturities) by estimating the Cumulative Abnormal CDS spread Returns (CAR). We estimate it using an event study methodology over a four-day event window ((-1,+2)), the event being the stress test results' disclosure.

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Table 3.9: Determinants of the market reaction to the disclosure of 3-year time horizon stress test results.

Market reaction	CAR [-1 ; 2]															
Horizons	3-year Scenario Time Horizon															
Scenarios	**Baseline**								**Adverse**							
Maturity	6-Month	1-Year	2-Year	3-Year	4-Year	5-Year	7-Year	10-Year	6-Month	1-Year	2-Year	3-Year	4-Year	5-Year	7-Year	10-Year
Stressed Indicators																
ΔCET1 Ratio	1.012	1.127	0.754	0.729	0.187	0.270	0.317	0.344	0.0208	-0.0939	-0.381	-0.375	-1.206	-1.223*	-0.475	-0.471
	(1.063)	(1.032)	(0.996)	(0.894)	(0.725)	(0.686)	(0.747)	(0.762)	(1.141)	(1.151)	(1.123)	(1.062)	(0.735)	(0.675)	(0.872)	(0.827)
ΔTotal Risk	2.789***	2.963***	2.927***	2.564***	1.769***	1.038	1.489*	1.650**	-0.506	-0.666	-0.397	-0.291	-0.193	-0.0693	-0.223	-0.123
	(0.853)	(0.850)	(0.917)	(0.837)	(0.657)	(0.679)	(0.766)	(0.790)	(0.725)	(0.817)	(0.767)	(0.632)	(0.414)	(0.363)	(0.495)	(0.546)
ΔP&L	-10.11**	-8.874**	-8.343*	-5.399	-1.036	0.136	-1.499	0.0983	-9.325**	-7.537	-6.204	-4.412	-0.363	0.653	-3.090	-0.630
	(4.136)	(4.156)	(4.173)	(3.752)	(2.675)	(2.753)	(3.495)	(3.716)	(4.579)	(4.633)	(4.535)	(3.862)	(2.719)	(2.541)	(3.904)	(3.650)
ΔNet Int Inc	-11.71**	-17.45***	-16.10**	-14.11**	-14.30**	-10.36	-5.282	-9.522*	6.926	0.337	-2.796	-3.982	-8.393	-10.15	5.422	-0.940
	(5.528)	(5.861)	(6.026)	(6.525)	(5.438)	(6.903)	(5.556)	(5.093)	(11.38)	(11.91)	(10.71)	(9.927)	(7.608)	(6.701)	(8.494)	(7.440)
ΔAccumul Inc	22.81	23.71*	27.19*	28.19**	17.92*	15.10	24.49*	23.42*	-6.341	-2.151	2.076	2.856	-2.308	-2.060	0.351	2.382
	(14.47)	(13.61)	(13.79)	(13.05)	(9.822)	(9.631)	(13.50)	(12.49)	(10.68)	(10.69)	(10.85)	(9.615)	(6.141)	(4.471)	(7.143)	(7.510)
Control Variables																
Leverage	1.807	2.700	2.034	1.185	1.240	0.677	1.359	0.975	1.808	2.899	2.607	2.217	2.749	2.334*	1.748	1.905
	(1.718)	(1.670)	(1.929)	(1.430)	(1.470)	(1.370)	(1.345)	(1.238)	(2.007)	(1.777)	(2.176)	(1.584)	(1.784)	(1.353)	(1.744)	(1.226)
Managmt Quality	-0.00325	-0.0151	0.00883	0.0475	-0.00294	0.00663	-0.0685	-0.0630	-0.0812	-0.105	-0.107	-0.0623	-0.0893	-0.0777	-0.145	-0.152
	(0.162)	(0.160)	(0.162)	(0.143)	(0.110)	(0.120)	(0.104)	(0.110)	(0.166)	(0.171)	(0.166)	(0.157)	(0.114)	(0.119)	(0.108)	(0.115)
Size	-0.0187	0.0622	0.117	0.127	0.00734	-0.0943	0.000117	0.0215	-0.175	-0.131	-0.0588	-0.0153	-0.0344	-0.0860	-0.0698	-0.0451
	(0.122)	(0.104)	(0.104)	(0.0956)	(0.0461)	(0.0592)	(0.0803)	(0.0911)	(0.178)	(0.162)	(0.150)	(0.124)	(0.0581)	(0.0545)	(0.0906)	(0.0970)
Funding Stability	-0.545	-0.326	-0.159	-0.134	0.115	-0.0521	-0.147	-0.177	-0.717	-0.574	-0.442	-0.339	0.0910	-0.0111	-0.217	-0.280
	(0.378)	(0.353)	(0.321)	(0.301)	(0.228)	(0.215)	(0.294)	(0.297)	(0.524)	(0.516)	(0.510)	(0.446)	(0.270)	(0.239)	(0.412)	(0.414)
Asset Quality	-0.937	-0.699	-0.706	-0.687	-0.939**	-1.028**	-1.155*	-1.043**	-1.230*	-1.021	-0.920	-0.805	-1.121**	-1.129**	-0.792	-0.931*
	(0.608)	(0.578)	(0.522)	(0.502)	(0.465)	(0.506)	(0.617)	(0.454)	(0.697)	(0.650)	(0.612)	(0.596)	(0.520)	(0.527)	(0.686)	(0.535)
Sensitivity Mkt Risk	-5.643	-3.036	-2.964	-3.270	-1.103	-2.073	-3.192	-3.677	-5.267	-2.648	-2.558	-2.427	-0.429	-0.998	-2.196	-2.952
	(5.816)	(3.975)	(3.531)	(3.416)	(2.552)	(2.556)	(3.492)	(3.399)	(5.991)	(4.928)	(4.596)	(4.151)	(2.270)	(1.940)	(3.371)	(3.629)

Liquidity	-0.0463	0.00311	-0.000749	0.00365	-0.0302	-0.0697	-0.0493	-0.0466	-0.0977	-0.0471	-0.0379	-0.0296	-0.0251	-0.0507	-0.0588	-0.0530
	(0.0797)	(0.0651)	(0.0664)	(0.0583)	(0.0505)	(0.0531)	(0.0495)	(0.0496)	(0.0986)	(0.0903)	(0.0946)	(0.0798)	(0.0587)	(0.0516)	(0.0596)	(0.0618)
Risk-Free Rate	2.945	1.311	0.466	-0.750	-1.900	-2.071**	-1.128	-1.436	3.558	1.843	0.877	-0.300	-1.023	-1.412	-0.574	-1.080
	(2.587)	(1.839)	(1.558)	(1.420)	(1.198)	(1.018)	(1.358)	(1.323)	(2.503)	(2.139)	(1.938)	(1.652)	(1.075)	(0.867)	(1.153)	(1.317)
Market Returns	-0.214	-0.235	-0.133	-0.0230	0.128	0.194	0.191*	0.103	-0.173	-0.191	-0.115	-0.0333	0.156*	0.206**	0.150*	0.0698
	(0.151)	(0.149)	(0.132)	(0.118)	(0.103)	(0.120)	(0.110)	(0.109)	(0.147)	(0.142)	(0.130)	(0.106)	(0.0833)	(0.0791)	(0.0805)	(0.0736)
Market Volatility	-8.966	-7.266	-3.385	0.280	0.636	-2.130	2.089	1.883	-8.146	-7.307	-2.843	0.549	2.049	-0.989	2.884	3.052
	(5.875)	(5.909)	(5.857)	(5.562)	(3.068)	(2.844)	(3.798)	(4.403)	(8.265)	(8.012)	(7.547)	(6.691)	(3.350)	(2.446)	(3.985)	(4.476)
Constant	-0.718	-3.888	-4.866	-4.413	-1.324	2.070	-1.051	-1.245	3.635	1.303	-0.469	-1.385	-1.642	0.220	0.500	-0.254
	(3.461)	(3.030)	(3.415)	(2.833)	(1.975)	(1.973)	(2.526)	(2.604)	(5.475)	(4.999)	(5.635)	(4.246)	(2.903)	(2.097)	(3.409)	(3.096)
Observations	108	106	106	109	107	109	107	109	108	106	106	109	107	109	107	109
R-squared	0.360	0.372	0.364	0.357	0.545	0.531	0.348	0.391	0.239	0.210	0.205	0.219	0.496	0.551	0.273	0.300
Adjusted R-squared	0.255	0.267	0.258	0.253	0.470	0.455	0.240	0.293	0.115	0.0781	0.0726	0.0927	0.413	0.479	0.154	0.187
Number of Banks	53	52	53	53	53	53	53	53	53	52	53	53	53	53	53	53
Prob. > F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.002	0.008	0.000	0	0.000	0.000
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustering	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Source: Authors' calculation.

Notes: This table reports the estimates from two distinct series of panel regressions. In each series, we regress the market reaction (to the divulgation of the 2014, 2016 and 2018 EU-wide stress test results) over a set of five stressed indicators and several control variables. These two series of regressions differ only in the stress test outcomes used to compute the five stressed indicators. For the series of regressions of the *baseline* scenario (*adverse* scenario), the stressed indicators are based solely on the *baseline* scenario outcomes (*adverse* scenario outcomes) estimated over a 3-year time horizon. Then, in each series, we have eight columns which present the estimates of eight distinct regressions that differ from each other only in the maturity used to calculate the market response (i.e. the dependent variable), following Agbodji *et al.* (2021) suggestions. We obtain the market reaction (at the level of all CDS maturities) by estimating the Cumulative Abnormal CDS spread Returns (CAR). We estimate it using an event study methodology over a four-day event window ((-1,+2)), the event being the stress test results' disclosure.
As stressed indicators, we have the **ΔCET1 Ratio** which is the Change in common equity tier 1 ratio caused by the simulated scenarios, scaled by total assets. **ΔTotal Risk** is the Change in total risk exposure amount caused by the simulated scenarios, scaled by total assets. **ΔP&L** is the Change in profit and losses caused by the simulated scenarios, scaled by total assets. **ΔNet Int Inc** is the Change in net interest income caused by the simulated scenarios, scaled by total assets. **ΔAccumul Income** is the Change in accumulated other income caused by the simulated scenarios, scaled by total assets. As control variables, we have the **Leverage** is the Ratio of liabilities to the sum of liabilities and equity. **Managmt Quality** is the Cost efficiency ratio (Ratio of operating expenses to total revenues). **Size** is the Natural logarithm of bank total assets. **Funding Stability** is the Ratio of deposits to total liabilities. **Asset Quality** is the Ratio of non-performing loans to total assets. **Sensitivity Mkt Risk** is the Cost of funds (i.e. Ratio of interest expense to total liabilities). **Liquidity** is the Ratio of net loans to deposits and short-term funding. **Risk-Free Rate** is the Yield on 10-year government bond. **Market Returns** is the Country stock market returns. **Market Volatility** is the Historical standard deviation of daily country market returns. Following Petersen (2009) suggestions and Hasan *et al.* (2014), we use bank fixed effects to account for unobserved time-invariant bank characteristics (that exist and have important explanatory power for the market reactions) and to improve the efficiency of our estimates. Robust standard errors (in parenthesis) are clustered by bank. *, **, *** indicate respectively significance at 10%, 5% and 1% levels.

3.4.1. *Baseline* Scenario vs. *Adverse* Scenario.

First of all, considering the adjusted R-squared, one can notice that the *baseline* regression series appear to better explain the variation in the market reactions (CARs), compared to the *adverse* scenario series. More precisely, considering the 1-year time horizon (Table 3.7), our model explains on average 34% of the variation in CARs when we consider the *baseline* scenario, with a maximum of 49%. For the *adverse* scenario, this rate drops to 22% with a maximum of 45%. For the 2-year time horizon (3-year time horizon), 35,7% (31,1%) of the variation in CARs is explained by our model for the *baseline* scenario, with a maximum of 52% (47%). This rate then drops to 21,3% (19,9%) with a maximum of 50% (48%) when we consider the *adverse* scenario.

Then, according to our results, whatever the time horizon considered, the impact of the *baseline* scenario on the participating banks' characteristics appears to be highly significant in driving the market reactions, unlike the impact of the *adverse* scenario. Indeed, our results show that whatever the time horizon, the market reactions are significantly determined by four of the five stressed indicators based on the *baseline* scenario outcomes. On the other hand, when we consider the *adverse* scenario outcomes, these indicators totally lose their explanatory power whatever the time horizon[43]. None of the five indicators significantly drives the market reactions in the vast majority of *adverse* cases[44]. Our results therefore suggest that the *adverse* scenario outcomes do not determine the market reactions, whatever the time horizon considered. By contrast, the *baseline* scenario outcomes significantly explain these reactions, which lead us to suggest that the market reactions to stress test results' disclosure may only be driven by the *baseline* scenario outcomes.

In view of these findings, we support that the 2014, 2016 and 2018 EU-wide stress testing exercises provide new and relevant information to market participants on the

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[43] This is all the more remarkable as the *adverse* scenario's impacts are more important than that of the *baseline* scenario. Indeed, analyzing the difference between the two scenarios' impact (with parametric and non-parametric tests), not surprisingly, we find that the impact of the *adverse* scenario is significantly and substantially more important than that of the *baseline* scenario, whatever the bank characteristic considered and whatever the time horizon.

[44] Effectively, in some *adverse* regressions, there may be a maximum of one stressed indicator that shows a moderate statistical significance, especially under the 1-year scenario.

tested banks' risks and financial situation. This information, that was not available to them until the release of the test results, does not seem to be generated by the two macroeconomic scenarios implemented, but only by the *baseline* scenario. Indeed, market participants seem to have drawn no new and relevant information on tested banks' risks and situation from the *adverse* scenario outcomes. According to our results, only the outcomes from the *baseline* scenario seem to have provided them with such information. They then priced the latter as reflected in the fact that the change in the banks' characteristics under this scenario significantly drives the abnormal changes in CDS spreads, unlike the changes under the *adverse* scenario. We therefore support that the informative content of the *baseline* and *adverse* scenario outcomes is not the same, whatever the scenario time horizon considered. According to our results, the *adverse* scenario seems to have no informative content, unlike the *baseline* scenario.

3.4.2. Short-Term CDS Maturities vs. Medium and Long-Term CDS Maturities

Moreover, our results evidence that the (*baseline*) pricing process described above is much more important and significant for the spreads of CDS of short-term maturities, compared to medium- or long-term spreads. Indeed, our findings show that the indicators' explanatory power is not the same for all maturities of CDS. In each of the tables 3.7, 3.8 and 3.9, one can notice that the market reactions over the three highest maturities (5-year, 7-year and 10-year) may be determined by the stressed indicators in general, but with moderate or no significance. As we can see in the tables, over these maturities, only two of the five indicators are moderately significant in driving the market reactions in most cases. On the other hand, four of the five indicators strongly and significantly drive the market reactions over the remaining maturities, especially over the three shortest maturities (6-month, 1-year and 2-year) which show very high significance. This is particularly the case in Table 3.7 and 3.9 which apply respectively to the 1-year and 3-year time horizons. Consequently, we support that the informative content of stress testing exercises differs depending on the investor time horizon as the information that makes market participants react (i.e. the information driving the market response) is not the same from one CDS maturity to another. More precisely, our results suggest that this informative content differs depending on whether one consider the short-term horizon (6-month, 1-year and 2-year CDS maturity) which seems to be the most provided in informational content, or the long-term horizon. This may be explained by the fact that the stress test outcomes only cover short-term horizons (from 1 to 3 years); hence, information provided are more robust and abundant over these short horizons, compared to the medium- or long-term horizons. This finding does not change whatever the scenario time horizon considered, thus suggesting that market participants give importance to the three scenario horizons and none is prioritized at the expense of the other.

3.4.3. What About the 5-year Maturity of CDS?

Among the eight maturities of CDS that we consider in our empirical investigations, the 5-year maturity is the one that is commonly used in the literature as it is generally considered to be the most liquid segment of the CDS market (among others, Völz & Wedow, 2011; Annaert *et al.*, 2013). However, according to our results, the market reaction over this maturity is by far the one that is less determined by the *baseline* scenario outcomes, whatever the scenario time horizon. Table 3.9 shows this particularly well since none of the five indicators significantly drive the market reaction over this maturity, while over the remaining ones, we have until four highly significant indicators especially when we consider the short-term maturities[45]. This finding is interesting insofar as it questions the sole use of the 5-year maturity in the study of the market reaction and its determinants (Ahnert *et al.*, 2018). Effectively, the only consideration of the 5-year maturity in our investigations would have led us to the conclusion that the market reaction is not determined by the disclosed stress test information. But this is clearly not the case as our results show it. Our findings therefore complement the works of Agbodji *et al.* (2021) as it shows that researchers must consider several maturities (especially short-term maturities) when investigating the market reaction to stress tests and the drivers of this reaction.

[45] This is confirmed by the two other tables where only one (Table 3.7) or two (Table 3.8) stressed indicators moderately drive the market reaction over the 5-year maturity whereas for the remaining maturities, we have until three (Table 3.7) or four (Table 3.8) significant indicators.

3.4.4. Determinants of Abnormal Movements in CDS Spreads (the market reaction).

3.4.4.1. Impact of Bank Stressed Indicators

In each of the tables 3.7, 3.8 and 3.9, all our stressed indicators have the expected sign except the change in common equity tier 1 ratio (*ΔCET1 Ratio*) which, however, is not statistically significant whatever the time horizon. More precisely, according to our results, a positive market reaction (so a decrease in the Cumulative Abnormal CDS spreads Returns CAR) is significantly associated with a decrease in the Total Risk Exposure Amount (*ΔTotal Risk*), whatever the CDS maturity considered and whatever the scenario time horizon. It is also significantly associated with an increase in Net interest Income (*ΔNet Int Inc*) but not at the level of all maturities. Indeed, whatever the scenario time horizon, the Net interest Income appear to be highly significant in driving a positive market reaction when increasing, except for the 5-year and 7-year CDS maturities. Also, as expected, an increase in Profit & Losses (*ΔP&L*) is significantly associated with a positive market reaction but not for all CDS maturities. According to our results, only the market reaction over the shortest maturities (6-month, 1-year and 2-year maturities) are predicted by the change in Profit & Losses, whatever the time horizon. Finally, when we consider the Accumulated other comprehensive income (*ΔAccumul Income*), our results show that it impacts positively the CARs over the 2-year and 3-year scenario time horizons. A decrease in this indicator is indeed significantly associated with a positive market reaction over all CDS maturities, except the 5-year.

3.4.4.2. The Specific Case of the Common Equity Tier 1 Ratio

However, the total absence of effect of the decrease in common equity tier 1 ratio on the market reaction, whatever the CDS maturity or the scenario time horizon is quite unanticipated. Indeed, in the large list of bank characteristics that were stressed, the common equity tier 1 ratio is the most important as it summarizes most factors captured by the stress testing exercises (initial capital ratio before the test, profitability expectations, credit and market losses, liquidity etc...). Also, EU stress tests are primarily focused on the assessment of the impact of risk drivers on the solvency of banks (EBA Methodological Note, 2016, p.13). Hence, one would have expected that the change in the common equity tier 1 ratio would determine the market reaction, which is not the case. This therefore suggests that the market reaction is not driven by the principal and most important stress test outcome, which capture and summarize each tested banks' situation throughout the three time horizons. We explain this finding as follows.

This paper is based on the 2014, 2016 and 2018 EU-wide stress testing exercises. In other words, it is performed over a period after the global financial crisis of 2007–2008 and the Great Recession that followed, and after the European debt crisis. European banks, which entered these crises with insufficient quantity and quality of capital were severely weakened[46]. Hence, to correct the weak capital regulation that existed and to reinforce banks, European regulators adopted the *Capital Requirements Regulation and Directive* (CRR/CRD IV package[47]) that transposed into EU law, the Basel III agreement. It has been formally applied since January 2014 and more importantly, from the 2014 stress test, it has been fully taken into account. The three stress tests that we consider in this paper were therefore carried out with EU banks that were very well capitalized, whether quantitatively or qualitatively. We show this in Appendix 3.E which reports the summary statistics of tested banks' capital ratios before and during the different tests. Panel A applies to the Common Equity Tier 1 ratio while Panel B applies to the Tier 1 capital ratio. In Panel C, we analyze the difference in these capital ratios between different periods using parametric and non-parametric tests. Regardless of the capital ratio considered, the results show that the level of capitalization of tested banks is considerably and significantly more important during the period from 2013 to 2018 (so during the 2014, 2016 and 2018 exercises), than during the period from 2009 to 2011 (i.e. during the 2010 and 2011 exercises)[48]. This was not due only to the CRR/CRD IV package because long before the implementation of its rules, tested banks were already well capitalized, for example in 2013 as we show it in Panel C.

[46] EU governments were forced to provide unprecedented support to banks in order to protect and preserve the whole financial system and the real economy.

[47] This is an important legislation that aims to decrease the likelihood that banks go insolvent by substantially strengthening the quantity and the quality of their capital (among other measures).

[48] The average Common Equity Tier 1 ratio (Tier 1 capital ratio) increases by 49% (39%).

Consequently, according to us, the change in common equity tier 1 ratio (which is by far the "flagship" indicator disclosed) does not determine the market reaction because of the high level of capitalization of tested banks. Indeed, with high equity capital, tested banks have a safety cushion capable of absorbing operating loss shocks, and thus ensuring a low risk of insolvency (i.e. bankruptcy). That may be why market participants do not react to the variation in this important ratio insofar as the risk of bankruptcy is kept under control.

3.5. Robustness Checks

In this section, we conduct some additional investigations to first test the robustness of our above analysis that attempt to explain the total absence of effect of the decrease in common equity tier 1 ratio. In a second phase, we test the robustness of results from our reference model.

3.5.1. The 2010 and 2011 Stress Testing Exercises

To test the robustness of our above analysis concerning the total absence of effect of the decrease in common equity tier 1 ratio in explaining the abnormal movements in CDS spreads after the 2014, 1016 and 2018 stress tests, we repeat our empirical investigations by considering the 2010 and 2011 stress testing exercises. The objective is to examine how the change in tested banks' capital ratio determined the market reaction in 2010 and 2011 where the level of capitalization of participating banks was significantly lower, compared to the period from 2014 to 2018. Furthermore, several tested banks were seriously undercapitalized during this period. Consequently, equity capital could not serve as a safety cushion absorbing the operating loss shocks, thus leading to a high risk of bankruptcy. We therefore expect that market participants will attribute importance to the change in banks' capital ratio, and that their reaction will be driven by it.

To perform this analysis, we employ a more parsimonious model primarily because of the limited number of banking characteristics that were stress tested, especially in 2010. More precisely, as stressed indicators, we consider as capital adequacy ratio the

" *Tier 1 ratio*" since it is the one that was stress tested in 2010. Then, we consider the change in the "*Total Risk Exposure Amount*". We do not consider the three remaining indicators since they were not stress tested during the 2010 exercise and/or the 2011 exercise. Secondly, because of the limited number of observations, we keep as control variables the ones that are the most significant, i.e. the "*Leverage*", the "*Funding Stability*", the "*Asset Quality*" and the "*Liquidity*". The results obtained are presented in the Panel A and B of Appendix 3.F. Considering the 2010 test results (Panel A), we can see that contrary to what has been found above, the *adverse* scenario regression series appear to better explain the variation in the market reactions (CARs), compared to the *baseline* scenario series. Secondly, the results show that the market reactions to stress test results' disclosure are driven not only by the *baseline* scenario outcomes, but also by the *adverse* scenario outcomes. More importantly, whatever the scenario, a positive market reaction (so a decrease in CARs) is significantly associated with an increase in the Tier 1 ratio (*ΔTier 1*), in particular when we consider the *adverse* scenario. Also, a positive market reaction is significantly associated with a decrease in the Total Risk Exposure Amount (*ΔTotal Risk*), whatever the scenario considered.

These findings show that in 2010, market participants considered and examined not only the *baseline* scenario outcomes, but also and in particular the *adverse* scenario outcomes that they will neglect from the 2014 test as we have shown above. According to us, the *adverse* scenario outcomes were considered by market participants during this test because 2010 was a year of great stress on financial markets. This is in fact one of the reasons that motivated the conduct of this test, the expectation of regulators being to reduce the banking opacity by providing relevant information to market participants on banks' financial health and strength, in an attempt to restore their confidence in the banking system. More precisely, in times of stress or panic (and this was the case in July 2010), the *adverse* scenario may be more credible because it is likely to materialize. Consequently, it will matter for market participants which will therefore analyze it. On the other hand, in times of calm, it will no longer have the same importance for market participants insofar as the probability of it occurring is much lower; this may explain the fact that from the 2014 test, the market reaction is no longer determined by it.

Moreover, market participants attached great importance to the change in tested banks' Tier 1 ratio in each of the two scenarios implemented while from the 2014 exercise, they completely neglected it. Also, according to us, the market reaction to stress test results' disclosure in 2010 may be significantly driven by the change in tested banks' Tier 1 ratio because of the weak level of banks' capitalization and therefore, the possible risk of bankruptcy. Then, from 2013, banks gradually recapitalized until they clearly exceeded the regulatory minimum set by the CRR/CRD IV rules in 2014. As we said it above, this high level of capitalization can act as a safety cushion absorbing the operating loss shocks, and thus ensures a low risk of bankruptcy. That may be why market participants' reactions following the disclosure of the 2014, 2016 and 2018 stress test results are not driven by the change in this ratio.

Finally, the current model being different from our main model, one would suspect that our findings when considering the 2010 stress test are only due to the model difference. So, to be sure that this is not the case, we have redone our main estimates (i.e. considering the 2014, 2016 and 2018 tests) using the parsimonious model. The results obtained are presented in Panel C of Appendix 3.F and as we can see, our conclusions do not change. In other words, from the 2014 test, market participants no longer consider the *adverse* scenario outcomes and their reactions no longer depend on the change in tested banks' capital ratio.

When considering the 2011 test results (Panel B), whatever the scenario considered, none of the regressions are statistically significant. This means that the market reaction to this test results' disclosure is not driven by any of the disclosed outcomes, but by other factors. This result is not surprising because around the event date (July, 18), financial markets (especially in Europe) were in deep depression due to several factors. In Europe, there was a financial panic that was generated by new concerns about European debt, Greece debt in particular. Added to this are the placing of Spanish debt under negative watch by Moody's, the concerns about the political situation in Italy, and uncertainties about a possible exclusion of Greece from the Euro, among others. In the United States, the panic on the financial markets were due, among others, to the domestic political and economic situation, to the debt which was placed under negative watch by Standard & Poor's which will end up terminating the country's

AAA rating in early August. All these stress factors around the disclosure date may explain why the released outcomes do not drive the market reaction.

3.5.2. Additional Robustness Checks

To check the reliability of results from our reference model (presented in Tables 7, 8 and 9), we perform some robustness tests by employing a number of different specifications regarding the dependent variable (the market reaction).

We first consider alternative event and estimation windows in the market reaction calculation process. More precisely, we consider the (t-2; t+2) event window and a shorter estimation window of 84-trading days (following Covi and Ambrosini, 2016).

On the one hand, the new results (from the alternative event and estimation windows) strongly confirm that whatever the time horizon considered, only the *baseline* scenario outcomes determine the market reactions, especially over short term CDS maturities. On the other hand, if we analyze how stressed indicators drive the market response, the new estimates when using the 84-trading days window are very similar to our results (almost the same), except for the impact of the Accumulated other comprehensive income (ΔAccumul Income). This latter loses its significance and no longer determines the reaction of the market, whatever the time horizon. Concerning the remaining stressed indicators, there is almost no change in the direction or the significance of their impact.

When using the market reaction calculated over the event window (t-2; t+2), the new estimates obtained are very close to our results. We notice some decrease or loss of significance at the level of some CDS maturities but in general, the results obtained are in line with our main findings.

3.6. Conclusion

In this paper, we are mainly interested in whether market participants derive new and relevant information from the *baseline* and the *adverse* scenarios' outcomes, considering the different time horizons. As the two scenarios are not designed and elaborated in the same way, we examine whether and how their disclosed outcomes each determines the abnormal movements in the CDS premium, and whether their informative content is identical or not considering the different time horizons. We based on the 2014, 2016 and 2018 EU-wide stress tests and insofar as the market reaction differs depending on the CDS maturity employed (Agbodji *et al.*, 2021), we consider in our empirical investigations not only the 5-year maturity, but also all the remaining CDS maturities. Then, after estimating the market response, we regress it on participating banks' stressed indicators and several control variables. These indicators, which are computed based on the stress test outcomes, measure the impact of the two stress test scenarios on tested banks' characteristics (*Common Equity Tier 1 Ratio, Total Risk Exposure Amount, Profit & Losses, Net interest Income and Accumulated other comprehensive income*), considering each time horizon.

Our results evidence that following the disclosure of European stress test results since the 2014 exercise, the market response is only driven by the *baseline* scenario stress test outcomes, whatever the scenario time horizon considered. Market participants seem to have drawn no new and relevant information on tested banks' risks and financial situation from the *adverse* scenario outcomes. This therefore suggests that the informative content of the *baseline* and the *adverse* scenario's outcomes is not the same as unlike the *baseline* scenario, the *adverse* scenario seems to have no informative content, whatever the scenario time horizon. Our results also suggest that the informative content of stress testing exercises differs depending on the time horizon as we evidence that the information driving the market response is not the same from one CDS maturity to another.

Furthermore, even if the common equity tier 1 ratio is the most important indicator as it summarizes most factors captured by the stress testing exercises, its variation at the end of the scenarios do not play any role in the response of market participants (whatever the time horizon), unlike the changes in the remaining indicators. This may be due to the current high level of tested banks' capitalization which ensure a low risk of insolvency, which was not the case at the beginning of stress testing exercises in 2010 where the economic climate was uncertain and tested banks were significantly less capitalized. As a result, market participants considered and reacted to the change in CET1 ratio under both the *baseline* and the *adverse* scenarios.

Tables

Table 3.1: Description, expected coefficient sign, and data sources of explanatory variables.

Explanatory variables	Notation	Description	Expected sign	Data Source
Stress test outcomes				
Common Equity Tier 1 Ratio	ΔCET1 Ratio	Change in common equity tier 1 ratio caused by the simulated scenarios, scaled by total assets	-	eba.europa.eu
Total Risk Exposure Amount	ΔTotal Risk	Change in total risk exposure amount caused by the simulated scenarios, scaled by total assets	+	eba.europa.eu
Profit & Losses	ΔP&L	Change in profit and losses caused by the simulated scenarios, scaled by total assets	-	eba.europa.eu
Net Interest Income	ΔNet Int Inc	Change in net interest income caused by the simulated scenarios, scaled by total assets	-	eba.europa.eu
Accumulated other comprehensive income	ΔAccumul Income	Change in accumulated other income caused by the simulated scenarios, scaled by total assets	+/-	eba.europa.eu
Bank-level characteristics				
Leverage	Leverage	Ratio of liabilities to the sum of liabilities and equity	+	Bankscope / BankFocus
Management quality	Managmt Quality	Cost efficiency ratio (Ratio of operating expenses to total revenues)	+	Bankscope / BankFocus
Size	Size	Natural logarithm of bank total assets	-	Bankscope / BankFocus
Funding stability	Funding Stability	Ratio of deposits to total liabilities	-	Bankscope / BankFocus
Asset quality	Asset Quality	Ratio of non-performing loans to total assets	+	Bankscope / BankFocus
Sensitivity to market risk	Sensitivity Mkt Risk	Cost of funds (i.e. Ratio of interest expense to total liabilities)	+	Bankscope / BankFocus
Liquidity	Liquidity	Ratio of net loans to deposits and short-term funding	+	Bankscope / BankFocus
Macroeconomics				
Risk-free interest rate	Risk-Free Rate	Yield on 10-year government bond	-	Bloomberg
Stock market returns	Market Returns	Country stock market returns	-	Bloomberg
Stock market volatility	Market Volatility	Historical standard deviation of daily country market returns	+	Bloomberg

Source: Authors

Table 3.2: 2-year time horizon correlation table for the *baseline* sample (below the diagonal) and the *adverse* sample (above the diagonal).

Variables	ΔCET1 Ratio	ΔTotal Risk	ΔP&L	ΔNet Int Inc	ΔAccumul Inc	Leverage	Managmt Quality	Size	Funding Stability	Asset Quality	Sensitivity Mkt Risk	Liquidity	Risk-Free Rate	Market Returns	Market Volatility
ΔCET1 Ratio		-0,219	-0,0641	0,0514	0,1157	0,078	-0,4358	0,0765	-0,1689	-0,3007	0,0529	0,2736	0,0354	0,0598	-0,1415
ΔTotal Risk	-0,1333		0,027	0,0267	0,119	0,2774	0,2255	0,3457	-0,2221	-0,4567	-0,0158	-0,254	-0,3165	-0,0907	-0,2069
ΔP&L	-0,3169	0,0256		0,372	0,1607	0,3166	0,2306	0,1262	-0,2633	0,0841	0,0794	0,0293	0,3489	0,0643	0,0856
ΔNet Int Inc	-0,1898	-0,095	0,2714		0,3449	0,2313	0,1368	0,1217	-0,1328	-0,1568	-0,0693	-0,0951	0,1267	0,1857	-0,1922
ΔAccumul Inc	0,0692	-0,1584	0,11	0,1742		0,3583	0,0593	0,1666	-0,2927	-0,2924	0,0639	0,0561	-0,0811	0,2787	-0,3265
Leverage	0,0521	0,0199	0,198	0,004	0,2412		0,084	0,5251	-0,5559	-0,4375	0,0272	-0,1962	-0,3337	-0,0423	-0,2881
Managmt Quality	-0,4934	0,1755	0,2496	0,1284	0,0223	0,084		0,0427	0,0495	0,1039	0,1549	-0,3916	0,1965	0,1193	0,0544
Size	0,2362	0,0648	0,0428	-0,1719	0,0922	0,5251	0,0427		-0,3254	-0,4918	-0,2679	-0,3528	-0,3633	-0,3051	-0,2888
Funding Stability	-0,0256	-0,083	-0,1394	-0,0034	-0,2002	-0,5559	0,0495	-0,3254		0,3301	-0,0006	-0,1136	0,2116	-0,048	0,053
Asset Quality	-0,4218	-0,2014	0,2358	0,1526	-0,0115	-0,4375	0,1039	-0,4918	0,3301		0,117	0,0329	0,596	0,3829	0,5119
Sensitivity Mkt Risk	-0,2982	0,0905	0,0337	-0,0677	0,1169	0,0272	0,1549	-0,2679	-0,0006	0,117		-0,0619	0,2136	0,2654	0,2187
Liquidity	0,2269	-0,0991	0,0518	0,0482	0,0441	-0,1962	-0,3916	-0,3528	-0,1136	0,0329	-0,0619		-0,0007	-0,0188	-0,0655
Risk-Free Rate	-0,4113	0,0162	0,398	0,1984	0,0332	-0,3337	0,1965	-0,3633	0,2116	0,596	0,2136	-0,0007		0,4093	0,4205
Market Returns	-0,2972	-0,0518	0,0599	0,2186	-0,0417	-0,0423	0,1193	-0,3051	-0,048	0,3829	0,2654	-0,0188	0,4093		0,0071
Market Volatility	-0,3439	0,0708	0,1339	-0,0122	0,0147	-0,2881	0,0544	-0,2888	0,053	0,5119	0,2187	-0,0655	0,4205	0,0071	

Source: Authors' calculation.

Table 3.3: Multicollinearity Diagnostics (Variance Inflation Factors analysis).

As stressed indicators, we have the **ΔCET1 Ratio** which is the Change in common equity tier 1 ratio caused by the simulated scenarios, scaled by total assets. **ΔTotal Risk** is the Change in total risk exposure amount caused by the simulated scenarios, scaled by total assets. **ΔP&L** is the Change in profit and losses caused by the simulated scenarios, scaled by total assets. **ΔNet Int Inc** is the Change in net interest income caused by the simulated scenarios, scaled by total assets. **ΔAccumul Income** is the Change in accumulated other income caused by the simulated scenarios, scaled by total assets. As control variables, we have the **Leverage** is the Ratio of liabilities to the sum of liabilities and equity. **Managmt Quality** is the Cost efficiency ratio (Ratio of operating expenses to total revenues). **Size** is the Natural logarithm of bank total assets. **Funding Stability** is the Ratio of deposits to total liabilities. **Asset Quality** is the Ratio of non-performing loans to total assets. **Sensitivity Mkt Risk** is the Cost of funds (i.e. Ratio of interest expense to total liabilities). **Liquidity** is the Ratio of net loans to deposits and short-term funding. **Risk-Free Rate** is the Yield on 10-year government bond. **Market Returns** is the Country stock market returns. **Market Volatility** is the Historical standard deviation of daily country market returns.

Variables	**Variance Inflation Factors (VIFs)**					
	1-year Scenario Horizon		2-year Scenario Horizon		3-year Scenario Horizon	
	Baseline	***Adverse***	***Baseline***	***Adverse***	***Baseline***	***Adverse***
ΔCET1 Ratio	1,61	1,84	2,01	2,03	1,92	2,01
ΔTotal Risk	1,20	1,52	1,22	1,77	1,19	1,60
ΔP&L	1,76	1,95	1,78	1,94	1,83	2,05
ΔNet Int Inc	1,24	1,33	1,29	1,48	1,27	1,56
ΔAccumul Inc	1,25	1,53	1,26	1,59	1,21	1,57
Leverage	2,51	2,49	2,44	2,43	2,42	2,50
Managmt Quality	1,62	1,56	1,61	1,62	1,54	1,56
Size	2,22	2,22	2,30	2,27	2,38	2,37
Funding Stability	1,96	1,99	1,93	1,92	1,92	1,92
Asset Quality	2,87	3,28	2,94	3,96	2,83	3,67
Sensitivity Mkt Risk	1,35	1,37	1,41	1,35	1,41	1,34
Liquidity	1,74	1,83	1,76	1,85	1,80	1,83
Risk-Free Rate	2,31	2,5	2,32	2,77	2,33	2,84
Market Returns	1,91	2,09	1,86	2,18	1,83	2,14
Market Volatility	1,92	1,89	1,93	1,90	1,95	1,91
Mean VIFs	**1,83**	**1,96**	**1,87**	**2,07**	**1,86**	**2,06**

Source: Authors' calculation.

Table 3.4: Summary statistics (in bps) of the market reaction (CARs) over all the CDS maturities.

This table presents the summary statistics (in bps) of the estimates of the market response to the disclosure of EU-wide stress test results, in the time period from 2014 to 2018 and at the level of all CDS maturities. **Market reaction** refers to the market response to the disclosure of tested banks outcomes. It is obtained by calculating the Cumulative Abnormal CDS spreads Returns (CARs) over a relevant window around the release date t (from t-1 to t+2). **Maturity** refers to the CDS maturity used to calculate the CARs. **N** is the number of observations. **Mean** is the average while **Median** is the 50th percentile. **SD** is the standard deviation. **Min** is the Minimum while **Max** is the Maximum. **p10** and **p90** correspond respectively to the 10th and 90th percentiles.

Market Reaction	Maturity	N	Mean	Median	SD	Min	Max	p10	p90
CARs	6-Month	112	-61,74	-162,67	763,19	-1904,40	1665,30	-934,44	881,97
	1-Year	110	-71,02	-155,19	738,74	-1904,40	1665,30	-862,80	920,08
	2-Year	110	-41,97	-91,90	723,14	-1904,40	1665,30	-814,17	882,83
	3-Year	113	-72,95	-139,59	694,33	-1904,40	1665,30	-814,75	718,01
	4-Year	111	-78,37	-56,82	591,68	-1904,40	1589,66	-619,28	535,68
	5-Year	113	-119,90	-85,44	593,82	-1904,40	1492,07	-620,88	546,37
	7-Year	111	-31,28	-47,86	596,93	-1904,40	1665,30	-644,99	641,22
	10-Year	113	-125,98	-151,95	622,57	-1904,40	1665,30	-827,01	538,71
	Total	893	-75,63	-91,07	666,81	-1904,40	1665,30	-781,06	670,45

Source: Authors' calculation.

Table 3.5: Summary statistics (in bps) of indicators based on stress test outcomes.

This table reports the summary statistics (in bps) of our stressed indicators that are based on stress test outcomes. **ΔCET1 Ratio** is the Change in common equity tier 1 ratio caused by the simulated scenarios, scaled by total assets. **ΔTotal Risk** is the Change in total risk exposure amount caused by the simulated scenarios, scaled by total assets. **ΔP&L** is the Change in profit and losses caused by the simulated scenarios, scaled by total assets. **ΔNet Int Inc** is the Change in net interest income caused by the simulated scenarios, scaled by total assets. **ΔAccumul Income** is the Change in accumulated other income caused by the simulated scenarios, scaled by total assets.
Panel A, B and C apply respectively to the 1-year, 2-year and 3-year scenario time horizon. In each panel, **Scenario** refers to the stress test scenario considered. **N** is the number of observations. **Mean** is the average while **Median** is the 50th percentile. **SD** is the standard deviation. **Min** is the Minimum while **Max** is the Maximum. **p10** and **p90** correspond respectively to the 10th and 90th percentiles.

Panel A: Summary statistics (in bps) of indicators based on the **1-year time horizon** stress test outcomes.

Time Horizon of Scenarios	Scenario	Stressed Variable	N	Mean	Median	SD	Min	Max	p10	p90
1 year	*Baseline*	ΔCET1 Ratio	111	14,60	11,26	54,11	-148,95	148,27	-36,12	83,94
		ΔTotal Risk	111	34,95	23,40	106,11	-447,13	645,53	-4,98	101,15
		ΔP&L	111	-2,88	-4,77	46,02	-164,44	158,59	-42,99	36,71
		ΔNet Int Inc	111	-1,06	-1,37	10,57	-23,91	58,42	-8,41	4,93
		ΔAccumul Inc	111	-0,18	0	5,84	-39,84	18,70	-4,04	3,66
	Adverse	ΔCET1 Ratio	111	-216,87	-201,81	119,01	-657,75	0	-374,54	-72,08
		ΔTotal Risk	111	175,19	141,31	169,62	-420,20	645,53	32,40	364,51
		ΔP&L	111	-55,93	-54,76	53,45	-164,44	98,11	-122,45	1,42
		ΔNet Int Inc	111	-11,02	-9,69	16,00	-75,69	58,42	-31,40	0
		ΔAccumul Inc	111	-15,81	-12,01	18,86	-53,44	18,70	-51,16	2,69

Source: Authors' calculation.

Panel B: Summary statistics (in bps) of indicators based on the **2-year time horizon** stress test outcomes.

Time Horizon of Scenarios	Scenarios	Stressed Variable	N	Mean	Median	SD	Min	Max	p10	p90
2 years	*Baseline*	ΔCET1 Ratio	111	40,86	45,97	98,12	-343,52	282,19	-68,93	163,29
		ΔTotal Risk	111	40,52	34,40	119,73	-495,28	645,53	-2,37	146,62
		ΔP&L	111	4,52	0,84	45,79	-164,44	158,59	-35,26	48,77
		ΔNet Int Inc	111	-2,05	-1,70	12,07	-30,43	58,42	-10,28	2,80
		ΔAccumul Inc	111	-0,16	0	6,47	-39,84	18,70	-4,30	3,84
	Adverse	ΔCET1 Ratio	111	-307,83	-277,17	142,41	-657,75	-1,55	-521,15	-145,94
		ΔTotal Risk	111	247,88	232,77	194,75	-432,39	645,53	34,44	477,75
		ΔP&L	111	-30,10	-32,56	48,13	-164,44	128,27	-83,51	14,74
		ΔNet Int Inc	111	-15,79	-13,84	18,43	-86,80	58,42	-36,12	0,00
		ΔAccumul Inc	111	-14,63	-9,83	18,87	-53,44	18,70	-49,33	6,61

Source: Authors' calculation.

Panel C: Summary statistics (in bps) of indicators based on the **3-year time horizon** stress test outcomes.

Time Horizon of Scenarios	Scenarios	Stressed Variable	N	Mean	Median	SD	Min	Max	p10	p90
3 years	*Baseline*	ΔCET1 Ratio	111	56,68	67,09	149,26	-578,93	352,53	-101,61	230,93
		ΔTotal Risk	111	49,58	47,30	135,37	-495,27	645,53	-6,17	173,58
		ΔP&L	111	5,07	1,59	46,76	-164,44	158,59	-35,20	52,83
		ΔNet Int Inc	111	-3,64	-2,74	13,84	-37,69	58,42	-15,72	1,48
		ΔAccumul Inc	111	-0,31	0	6,79	-39,84	18,70	-5,21	3,84
	Adverse	ΔCET1 Ratio	111	-366,02	-339,04	164,22	-657,75	-0,96	-635,66	-179,51
		ΔTotal Risk	111	264,27	262,89	208,69	-289,74	645,53	10,65	530,31
		ΔP&L	111	-27,08	-28,89	49,38	-164,44	127,11	-78,88	18,40
		ΔNet Int Inc	111	-20,28	-18,35	20,44	-91,99	58,42	-48,34	-1,85
		ΔAccumul Inc	111	-15,75	-11,30	19,57	-53,44	18,70	-51,16	4,43

Source: Authors' calculation.

Table 3.6: Summary statistics of control variables.

This Table presents the summary statistics of our model control variables, in the time period from 2013 to 2017. **Leverage** is the Ratio of liabilities to the sum of liabilities and equity. **Managmt Quality** is the Cost efficiency ratio (Ratio of operating expenses to total revenues). **Size** is the Natural logarithm of bank total assets. **Funding Stability** is the Ratio of deposits to total liabilities. **Asset Quality** is the Ratio of non-performing loans to total assets. **Sensitivity Mkt Risk** is the Cost of funds (i.e. Ratio of interest expense to total liabilities). **Liquidity** is the Ratio of net loans to deposits and short-term funding. **Risk-Free Rate** is the Yield on 10-year government bond. **Market Returns** is the Country stock market returns. **Market Volatility** is the Historical standard deviation of daily country market returns.
Considering each row, **N** is the number of observations. **Mean** is the average while **Median** is the 50th percentile. **SD** is the standard deviation. **Min** is the Minimum while **Max** is the Maximum. **p10** and **p90** correspond respectively to the 10th and 90th percentiles.

Control Variable	N	Mean	Median	SD	Min	Max	p10	p90
Leverage	110	0,935	0,937	0,016	0,882	0,962	0,914	0,953
Managmt Quality	110	0,630	0,622	0,166	-0,033	1,275	0,472	0,797
Size	110	26,746	26,585	1,030	24,224	28,546	25,448	28,144
Funding Stability	110	0,472	0,461	0,136	0,232	0,844	0,286	0,654
Asset Quality	110	0,050	0,026	0,055	0,000	0,196	0,007	0,142
Sensitivity Mkt Risk	110	0,015	0,012	0,012	0,003	0,057	0,005	0,026
Liquidity	110	0,898	0,878	0,244	0,382	1,934	0,604	1,214
Risk-Free Rate	110	0,021	0,017	0,016	0,004	0,062	0,006	0,046
Market Returns	110	0,151	0,156	0,095	-0,072	0,336	0,061	0,280
Market Volatility	110	0,010	0,009	0,003	0,005	0,019	0,006	0,015

Source: Authors' calculation.

Appendix 3

Appendix 3.A: Participating banks and Countries included in our final sample.

Considering a given stress test column, × indicates tested banks with available data on tradable credit default swap (so banks with available CDS spread returns). Hence, it indicates banks that we consider to examine the impacts of the test.

Panel A: List of participating banks included in our final sample, test by test

Bank Name	Bank Country	2014 EBA test	2016 EBA test	2018 EBA test
ABN AMRO Bank NV	NETHERLANDS	×		×
Allied Irish Banks plc	IRELAND	×	×	×
Alpha Bank AE	GREECE	×		
Banca Monte dei Paschi di Siena SpA	ITALY	×	×	
Banca Popolare di Milano SCaRL	ITALY	×		
Banco Bilbao Vizcaya Argentaria SA	SPAIN	×	×	×
Banco BPI SA	PORTUGAL	×		
Banco BPM SpA	ITALY			×
Banco Comercial Português, SA-Millennium bcp	PORTUGAL	×		
Banco de Sabadell SA	SPAIN	×	×	×
Banco Popolare - Società Cooperativa-Banco Popolare	ITALY	×	×	
Banco Popular Espanol SA	SPAIN	×	×	
Banco Santander SA	SPAIN	×	×	×
BAWAG PSK Bank fuer Arbeit und Wirtschaft und OP AG	AUSTRIA	×		
Bank of Ireland	IRELAND	×	×	×
Bankinter SA	SPAIN	×		
Barclays Bank Plc	BRITAIN	×	×	×
Bayerische Landesbank	GERMANY	×	×	
BNP Paribas	FRANCE	×	×	×
Caixa Geral de Depositos	PORTUGAL	×		
CaixaBank SA	SPAIN			×
Commerzbank AG	GERMANY	×	×	
Cooperatieve Rabobank U.A.	NETHERLANDS		×	×
Crédit Agricole S.A.	FRANCE	×	×	×
Danske Bank A/S	DENMARK	×	×	×
Deutsche Bank AG	GERMANY	×	×	
DNB Bank ASA	NORWAY	×	×	×
DZ Bank AG-Deutsche Zentral-Genossenschaftsbank	GERMANY	×		×
Erste Group Bank AG	AUSTRIA	×	×	×
Eurobank Ergasias SA	GREECE	×		
HSBC Bank plc	BRITAIN	×	×	×
HSH Nordbank AG	GERMANY	×		
IKB Deutsche Industriebank AG	GERMANY	×		
ING Bank NV	NETHERLANDS	×	×	×
Intesa Sanpaolo	ITALY	×	×	×
KBC Groep NV/ KBC Groupe SA-KBC Group	BELGIUM	×	×	×

Landesbank Baden-Wuerttemberg	GERMANY	×	×	
Landesbank Hessen-Thueringen Girozentrale - HELABA	GERMANY	×	×	
Lloyds Bank Plc	BRITAIN	×	×	×
Mediobanca Banca di Credito Finanziario SpA	ITALY	×		
National Bank of Greece SA	GREECE	×		
Norddeutsche Landesbank Girozentrale NORD/LB	GERMANY	×	×	
Nordea Bank AB (publ)	SWEDEN	×	×	×
Permanent Tsb Group Holdings P.L.C	IRELAND	×		
Piraeus Bank SA	GREECE	×		
Raiffeisen Bank International AG	AUSTRIA			×
Royal Bank of Scotland Group Plc (The)	BRITAIN	×	×	×
Skandinaviska Enskilda Banken AB	SWEDEN	×	×	×
Société Générale SA	FRANCE	×	×	×
Svenska Handelsbanken	SWEDEN	×	×	×
Swedbank AB	SWEDEN	×	×	×
UniCredit SpA	ITALY	×	×	×
Unione di Banche Italiane Scpa-UBI Banca	ITALY	×	×	×
Total number of EU banks included in our study sample		**49**	**33**	**30**
Total number of EU banks covered by the stress test		**123**	**51**	**48**
The share of the total assets of banks included in our study sample compared to that of banks covered by the stress test		**77,75%**	**81,73%**	**77,01%**

Sources: European Banking Authority (EBA) and Authors' calculation.
Notes: All the above companies are **banks**. To calculate the shares, we collect annual data on Total Assets from Bankscope Fitch IBCA and BankFocus (for the 2018 test), for all EU banks covered by our considered stress tests.

Panel B: Different countries in the EU final sample

Country	**Number of banks**
Austria	3
Belgium	1
Britain	4
Denmark	1
France	3
Germany	9
Greece	4
Ireland	3
Italy	8
Netherlands	3
Norway	1
Portugal	3
Spain	6
Sweden	4
Total number of participating banks	**53**

Sources: European Banking Authority (EBA) and Authors' calculation.

Appendix 3.B: Summary statistics of the absolute Bid-Ask spreads (CDS liquidity proxy).

To measure the liquidity of the different maturities of CDS contract, following Tang and Yan (2013), Annaert *et al.* (2013) and Samaniego-Medina *et al.* (2016), we use the absolute Bid-Ask spread of the CDS quotes, i.e. the difference between ask and bid quotes. As liquidity increases, the size of the bid-ask spread narrows.

In this appendix, considering our sample of 53 listed euro area banks, we provide the summary statistics of the absolute bid-ask spreads (BAS) at the level of each year from 2010 to 2018. In each Panel, **N** is the number of observations. **Mean** (**SD**) is the average (standard deviation). **BAS_Ratio** corresponds to the Mean BAS of a maturity divided by that of the 5-Year maturity. This will allow us to compare the liquidity of the different maturities with each other. A BAS Ratio equal to 1 means that the maturity is as liquid as the 5-year maturity. When higher (lower) than one, this means that the maturity is less (more) liquid than the 5-year maturity.

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
	6-Month	12136	34,6	47,9	17,2	2,3
	1-Year	11669	30,8	42,0	15,5	2,1
2	2-Year	11669	24,7	30,5	13,9	1,7
0	3-Year	12191	19,6	23,0	11,9	1,3
1	4-Year	11408	17,2	18,4	11,0	1,2
0	5-Year	12191	14,9	15,7	10,0	1,0
	7-Year	11669	14,4	14,9	9,3	1,0
	10-Year	12191	13,9	14,7	9,8	0,9
	All	95124	21,3	29,6	11,3	

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
	6-Month	11901	78,4	137,2	30,0	2,2
	1-Year	11381	74,9	135,8	27,1	2,1
2	2-Year	11381	55,9	91,1	23,4	1,6
0	3-Year	11901	43,6	70,1	19,4	1,2
1	4-Year	11197	40,3	67,7	17,3	1,1
1	5-Year	11903	35,8	66,7	15,0	1,0
	7-Year	11381	35,6	72,1	14,3	1,0
	10-Year	11901	35,7	82,2	13,3	1,0
	All	92946	50,0	96,0	18,9	

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
	6-Month	12030	106,0	216,5	37,5	2,4
	1-Year	11508	90,9	168,0	35,1	2,0
2	2-Year	11508	67,3	107,7	30,7	1,5
0	3-Year	12030	55,8	95,9	24,6	1,2
1	4-Year	11508	51,1	87,6	21,9	1,1
2	5-Year	12030	44,9	84,2	20,0	1,0
	7-Year	11508	48,1	91,4	20,0	1,1
	10-Year	12030	50,0	100,7	20,4	1,1
	All	94152	64,2	129,0	25,4	

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
	6-Month	12450	49,7	101,6	17,9	1,9
	1-Year	11928	51,3	100,4	19,9	2,0
2	2-Year	11928	41,5	66,2	20,0	1,6
0	3-Year	12450	35,1	52,8	20,0	1,3
1	4-Year	11922	32,2	44,3	20,0	1,2
3	5-Year	12450	26,2	38,4	16,7	1,0
	7-Year	11928	27,1	33,5	18,7	1,0
	10-Year	12450	26,1	32,0	18,4	1,0
	All	97506	36,1	65,1	19,4	

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
	6-Month	13406	22,9	39,0	10,8	1,4
	1-Year	12884	23,6	35,4	11,5	1,5
2	2-Year	12884	22,2	24,5	13,4	1,4
0	3-Year	13406	20,4	20,8	13,4	1,3
1	4-Year	12884	18,9	17,9	11,7	1,2
4	5-Year	13406	16,3	17,1	10,0	1,0
	7-Year	12884	19,4	16,8	13,3	1,2
	10-Year	13406	19,2	16,0	14,3	1,2
	All	105160	20,3	25,0	11,7	

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
	6-Month	13572	72,5	367,7	12,9	0,9
	1-Year	13236	68,9	305,1	12,2	0,8
2	2-Year	13435	84,6	366,5	13,7	1,0
0	3-Year	13560	94,7	443,1	13,7	1,1
1	4-Year	13446	85,3	409,0	10,6	1,0
5	5-Year	13572	83,2	418,6	10,0	1,0
	7-Year	13434	125,0	849,8	12,0	1,5
	10-Year	13572	101,0	533,3	13,8	1,2
	All	107827	89,4	488,7	12,1	

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
	6-Month	13572	71,5	186,6	15,0	1,1
	1-Year	13311	70,9	188,2	14,5	1,0
2	2-Year	13572	85,0	280,1	14,9	1,2
0	3-Year	13572	79,5	240,4	14,1	1,2
1	4-Year	13572	72,4	221,2	13,7	1,1
6	5-Year	13572	68,0	208,8	11,7	1,0
	7-Year	13572	62,6	177,5	15,6	0,9
	10-Year	13572	70,1	220,9	16,9	1,0
	All	108315	72,5	217,9	14,9	

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
	6-Month	13007	52,9	134,3	9,5	0,9
	1-Year	12965	52,6	130,3	10,0	0,9
2	2-Year	13225	52,3	134,4	10,5	0,9
0	3-Year	13225	64,3	180,2	10,4	1,1
1	4-Year	13225	59,2	168,0	9,9	1,0
7	5-Year	13225	57,8	169,1	9,8	1,0
	7-Year	13225	65,6	195,7	12,1	1,1
	10-Year	13225	81,5	290,4	14,2	1,4
	All	105322	60,8	182,4	10,6	

Year	Maturity	N	Mean	SD	Median	BAS_Ratio
	6-Month	13572	43,4	115,9	7,4	0,9
	1-Year	13572	46,6	120,9	8,0	1,0
2	2-Year	13572	46,2	122,2	8,5	1,0
0	3-Year	13572	54,5	150,3	9,8	1,1
1	4-Year	13572	50,0	140,4	7,2	1,0
8	5-Year	13572	47,8	138,2	5,7	1,0
	7-Year	13572	52,7	145,7	10,0	1,1
	10-Year	13572	58,5	184,6	10,0	1,2
	All	108576	50,0	141,4	9,2	

Source: Authors' calculation.

Appendix 3.C: Estimating the dependent variable CARs.

To capture the market response to the publication of banking stress test results, we calculate the Cumulative Abnormal CDS spreads Returns (CAR) over a relevant window around the disclosure date ("*event window*"). More precisely, we proceeded as follows.

(i) *Events and Event window*

In this paper, we consider as "event" the stress test results' disclosure. Also, since the results are published after market close, we do not consider the date of the disclosure as the event date, but rather the next available trading day following Petrella and Resti (2013), Flannery *et al.* (2017), Ahnert *et al.* (2018) and Agbodji *et al.* (2021).

As event window, we focus on a four-day window (t-1, t, t+1, t+2). Indeed, unlike Petrella and Resti (2013), we decide to take into account at least the trading day before the event date in order to incorporate the risk of a news leak before the disclosure.

(ii) *Estimating the abnormal return* $AR_{i,t}$

To obtain the Cumulative Abnormal (CDS spreads) Returns of a bank i (CAR_i), we measure first its abnormal return $AR_{i,t}$ over each date t of the event window. It is the difference between the observed CDS spread return $R_{i,t}$ and the return that would be expected if the event did not take place $\hat{R}_{it}$ ($AR_{i,t} = R_{i,t} - \hat{R}_{it}$). To estimate the latter, following the recent stress test literature (Campbell *et al.*, 2010; Morgan *et al.*, 2014; Sahin *et al.*, 2020; Flannery *et al.*, 2017 and Ahnert *et al.*, 2018; Agbodji *et al.*, 2021), we use a single-factor market model[49] ($R_{i,t} = \alpha_i + \beta_i . R_{m(i),t} + \varepsilon_{i,t}$) over a 120-trading days window (consistent with MacKinlay (1997) suggestion and following Alves *et al.*, 2015; Flannery *et al.*, 2017 and Ahnert *et al.*, 2018; Agbodji *et al.*, 2021). This window ends 10 trading days before the event as it goes from t-130 to t-11. In the market model, $R_{i,t}$ is the daily CDS spread return of bank i, on day t while $R_{m(i),t}$ is the daily CDX spread return of bank i's index, on day t. Following Morgan *et al.* (2014), Flannery *et al.* (2017)

[49] Ahern (2009) show that multifactor models produce only marginal benefits over a one-factor market model in predicting event day normal returns. This motivated us to use a one-factor market model, like several previous papers.

and Agbodji *et al.* (2021), we compute them by transforming into logarithmic returns the MID spreads of CDS (CDX)[50].

To compute the returns ($R_{i,t}$ and $R_{m(i),t}$), we collect daily data on senior CDS spread from the Bloomberg terminal, for each of the participating banking institutions in our study sample and for all CDS maturities. Then, as Indices for bank CDS, following Norden and Weber (2004), Morgan *et al.* (2014), Sahin *et al.* (2020), Flannery *et al.* (2017), Ahnert *et al.* (2018) and Agbodji *et al.* (2021), we employ the *Markit iTraxx Europe Investment Grade index* of which we also collect daily data from the Bloomberg terminal, but not for all maturities. Indeed, only four maturities are available (3, 5, 7 and 10 years). Therefore, following Agbodji *et al.* (2021), we first compute the 4Y daily CDX spreads by taking the average between the 3Y and the 5Y CDX spreads, at the level of each date. Secondly, for the remaining unavailable maturities (6-month, 1-year and 2-year), we assigned them the spreads of the nearest available maturity to perform our investigations (so the spreads of the 3-year maturity).

(iii) *Calculating the Cumulative Abnormal Returns (CAR_i)*

Finally, we calculate the Cumulative Abnormal (CDS spreads) Returns CAR_i by summing the Abnormal Returns AR_{it} over our four-day event window. Considering each stress test, we perform this computation for each participating bank.

As mentioned above, insofar as the CDS market reacts differently to the disclosure depending on the maturity of the CDS contract (Agbodji *et al.*, 2021), we compute different CARs considering each of the eight CDS maturities. Put another way, for each participating bank of each stress test, we estimate eight different market reactions (one estimate by CDS maturity).

[50] The MID spread of CDS (CDX) corresponds to the average between the BID and the ASK CDS (CDX) quotes

Appendix 3.D: 1-year and 3-year time horizon correlation tables for the *baseline* sample and the *adverse* sample.

As stressed indicators, we have the **ΔCET1 Ratio** which is the Change in common equity tier 1 ratio caused by the simulated scenarios, scaled by total assets. **ΔTotal Risk** is the Change in total risk exposure amount caused by the simulated scenarios, scaled by total assets. **ΔP&L** is the Change in profit and losses caused by the simulated scenarios, scaled by total assets. **ΔNet Int Inc** is the Change in net interest income caused by the simulated scenarios, scaled by total assets. **ΔAccumul Income** is the Change in accumulated other income caused by the simulated scenarios, scaled by total assets. As control variables, we have the **Leverage** is the Ratio of liabilities to the sum of liabilities and equity. **Managmt Quality** is the Cost efficiency ratio (Ratio of operating expenses to total revenues). **Size** is the Natural logarithm of bank total assets. **Funding Stability** is the Ratio of deposits to total liabilities. **Asset Quality** is the Ratio of non-performing loans to total assets. **Sensitivity Mkt Risk** is the Cost of funds (i.e. Ratio of interest expense to total liabilities). **Liquidity** is the Ratio of net loans to deposits and short-term funding. **Risk-Free Rate** is the Yield on 10-year government bond. **Market Returns** is the Country stock market returns. **Market Volatility** is the Historical standard deviation of daily country market returns.

Panel A: 1-year time horizon correlation table for the *baseline* sample (below the diagonal) and the *adverse* sample (above the diagonal).

Variables	**ΔCET1 Ratio**	**ΔTotal Risk**	**ΔP&L**	**ΔNet Int Inc**	**ΔAccumul Inc**	**Leverage**	**Managmt Quality**	**Size**	**Funding Stability**	**Asset Quality**	**Sensitivity Mkt Risk**	**Liquidity**	**Risk-Free Rate**	**Market Returns**	**Market Volatility**
ΔCET1 Ratio		-0,296	0,304	0,003	0,023	-0,023	-0,342	-0,119	-0,076	-0,066	0,195	0,290	0,215	0,214	-0,018
ΔTotal Risk	-0,161		-0,027	0,039	0,125	0,220	0,272	0,271	-0,277	-0,329	-0,014	-0,240	-0,193	-0,032	-0,089
ΔP&L	-0,176	0,052		0,261	0,155	0,376	0,113	0,128	-0,335	0,058	0,186	0,084	0,315	0,190	0,063
ΔNet Int Inc	-0,118	-0,047	0,265		0,300	0,176	0,150	0,138	-0,096	-0,117	-0,054	-0,117	0,161	0,176	-0,153
ΔAccumul Inc	0,031	-0,022	0,131	0,202		0,346	0,056	0,188	-0,293	-0,324	0,046	0,047	-0,155	0,232	-0,313
Leverage	0,005	0,018	0,278	0,021	0,221		0,084	0,525	-0,556	-0,438	0,027	-0,196	-0,334	-0,042	-0,288
Managmt Quality	-0,469	0,205	0,250	0,093	0,030	0,084		0,043	0,050	0,104	0,155	-0,392	0,197	0,119	0,054
Size	0,155	0,065	0,125	-0,065	0,087	0,525	0,043		-0,325	-0,492	-0,268	-0,353	-0,363	-0,305	-0,289
Funding Stability	-0,021	-0,155	-0,182	-0,018	-0,217	-0,556	0,050	-0,325		0,330	-0,001	-0,114	0,212	-0,048	0,053
Asset Quality	-0,365	-0,151	0,132	0,107	-0,002	-0,438	0,104	-0,492	0,330		0,117	0,033	0,596	0,383	0,512
Sensitivity Mkt Risk	-0,207	0,046	0,044	-0,045	0,132	0,027	0,155	-0,268	-0,001	0,117		-0,062	0,214	0,265	0,219
Liquidity	0,191	-0,096	0,029	-0,008	0,042	-0,196	-0,392	-0,353	-0,114	0,033	-0,062		-0,001	-0,019	-0,066
Risk-Free Rate	-0,306	0,038	0,328	0,123	0,060	-0,334	0,197	-0,363	0,212	0,596	0,214	-0,001		0,409	0,421
Market Returns	-0,278	-0,009	0,035	0,194	-0,057	-0,042	0,119	-0,305	-0,048	0,383	0,265	-0,019	0,409		0,007
Market Volatility	-0,241	0,092	0,060	-0,040	0,038	-0,288	0,054	-0,289	0,053	0,512	0,219	-0,066	0,421	0,007	

Source: Authors' calculation.

Panel B: 3-year time horizon correlation table for the *baseline* sample (below the diagonal) and the *adverse* sample (above the diagonal).

Variables	**ΔCET1 Ratio**	**ΔTotal Risk**	**ΔP&L**	**ΔNet Int Inc**	**ΔAccumul Inc**	**Leverage**	**Managmt Quality**	**Size**	**Funding Stability**	**Asset Quality**	**Sensitivity Mkt Risk**	**Liquidity**	**Risk-Free Rate**	**Market Returns**	**Market Volatility**
ΔCET1 Ratio		-0,0811	-0,0347	0,0917	0,1744	0,2193	-0,3957	0,2313	-0,2748	-0,3981	-0,0953	0,2451	-0,0731	0,0201	-0,265
ΔTotal Risk	-0,0986		-0,0387	0,0494	0,0971	0,2538	0,1527	0,3511	-0,112	-0,4642	-0,0607	-0,2038	-0,3723	-0,1315	-0,2825
ΔP&L	-0,3208	-0,0227		0,3981	0,1529	0,3307	0,2678	0,1638	-0,2682	0,0634	0,0471	-0,0092	0,3552	0,0573	0,0676
ΔNet Int Inc	-0,1245	-0,0804	0,2572		0,3496	0,3171	0,1129	0,1361	-0,2059	-0,2389	-0,0927	-0,0545	0,0429	0,1446	-0,2427
ΔAccumul Inc	0,0235	-0,1725	0,1258	0,1424		0,3933	0,0344	0,1887	-0,3055	-0,3113	0,0345	0,066	-0,1541	0,237	-0,347
Leverage	0,0673	0,0365	0,1989	0,0053	0,2578		0,084	0,5251	-0,5559	-0,4375	0,0272	-0,1962	-0,3337	-0,0423	-0,2881
Managmt Quality	-0,4582	0,1309	0,2676	0,0911	0,0225	0,084		0,0427	0,0495	0,1039	0,1549	-0,3916	0,1965	0,1193	0,0544
Size	0,2594	0,1212	0,0375	-0,2001	0,1053	0,5251	0,0427		-0,3254	-0,4918	-0,2679	-0,3528	-0,3633	-0,3051	-0,2888
Funding Stability	-0,0391	-0,035	-0,1484	-0,0376	-0,2064	-0,5559	0,0495	-0,3254		0,3301	-0,0006	-0,1136	0,2116	-0,048	0,053
Asset Quality	-0,4028	-0,2249	0,2423	0,128	-0,0219	-0,4375	0,1039	-0,4918	0,3301		0,117	0,0329	0,596	0,3829	0,5119
Sensitivity Mkt Risk	-0,3244	0,0432	0,0409	-0,0806	0,0937	0,0272	0,1549	-0,2679	-0,0006	0,117		-0,0619	0,2136	0,2654	0,2187
Liquidity	0,2348	-0,1013	0,053	0,1124	0,0446	-0,1962	-0,3916	-0,3528	-0,1136	0,0329	-0,0619		-0,0007	-0,0188	-0,0655
Risk-Free Rate	-0,4013	-0,0278	0,4143	0,1782	0,0026	-0,3337	0,1965	-0,3633	0,2116	0,596	0,2136	-0,0007		0,4093	0,4205
Market Returns	-0,251	-0,1031	0,0883	0,2229	-0,0512	-0,0423	0,1193	-0,3051	-0,048	0,3829	0,2654	-0,0188	0,4093		0,0071
Market Volatility	-0,3842	0,0325	0,1341	-0,043	-0,0076	-0,2881	0,0544	-0,2888	0,053	0,5119	0,2187	-0,0655	0,4205	0,0071	

Source: Authors' calculation.

Appendix 3.E: Summary statistics of tested banks' Capital Ratio before and during the tests.

This appendix reports the summary statistics of tested banks' capital ratios before and during the different stress tests. Panel A applies to the *Common Equity Tier 1 ratio* while Panel B applies to the *Tier 1 ratio*. **For the year 2009 in Panel A, we only have 21 observations due to unavailable data on the Common Equity Tier 1 ratio of some banks**.
In Panel C, we analyze the difference in these capital ratios between different periods using parametric and non-parametric tests. As parametric test, we employ the *Two-sample T test* while as non-parametric tests, we employ the *Two-sample Wilcoxon rank-sum (Mann-Whitney) test* and *the Kruskal-Wallis equality-of-populations rank test*. Whatever the test used, all the difference in this Panel are highly significant (p-value always equal to 0).

Panel A: Summary statistics of tested banks' **Common Equity Tier 1 Ratio.**

Stress Test	Year	N	Mean	Median	SD	Min	Max	p10	p90
2010 Exercise	2009	21	8,60%	8,50%	1,49%	6,40%	12,40%	7,10%	10,70%
	2010	41	8,70%	8,70%	1,84%	3,82%	12,60%	6,18%	10,80%
2011 Exercise	2010	40	8,81%	8,70%	1,70%	3,82%	12,60%	6,44%	10,85%
	2011	40	9,45%	9,38%	1,84%	3,82%	15,10%	8,17%	11,10%
2014 Exercise	2013	50	12,19%	11,78%	2,36%	7,10%	18,70%	9,85%	15,50%
	2014	50	12,65%	11,95%	2,54%	8,67%	21,20%	10,23%	15,95%
2016 Exercise	2015	33	13,91%	13,15%	3,08%	9,60%	24,10%	10,90%	16,50%
	2016	33	13,54%	12,62%	3,90%	8,15%	25,10%	10,20%	18,40%
2018 Exercise	2017	30	14,75%	13,50%	3,46%	10,84%	24,60%	11,48%	19,45%
	2018	30	14,00%	13,45%	2,30%	10,90%	18,40%	11,40%	17,15%

Source: Authors' calculation.

Panel B : Summary statistics of tested banks' **Tier 1 Ratio.**

Stress Test	Year	N	Mean	Median	SD	Min	Max	p10	p90
2010 Exercise	2009	41	10,06%	9,80%	1,81%	7,20%	14,10%	7,96%	12,80%
	2010	41	10,44%	10,54%	2,34%	4,30%	15,70%	7,47%	12,90%
2011 Exercise	2010	40	10,59%	10,54%	2,15%	5,60%	15,70%	7,92%	13,20%
	2011	40	10,91%	10,55%	2,42%	4,20%	17,00%	8,80%	14,03%
2014 Exercise	2013	50	13,25%	12,70%	2,56%	7,82%	19,60%	10,60%	16,95%
	2014	50	13,56%	12,90%	2,78%	8,67%	22,40%	10,85%	16,85%
2016 Exercise	2015	33	15,22%	13,80%	3,58%	11,50%	26,90%	12,08%	19,10%
	2016	33	15,15%	13,90%	4,47%	8,17%	28,70%	11,53%	20,70%
2018 Exercise	2017	30	16,44%	15,08%	3,92%	11,56%	27,30%	12,48%	21,95%
	2018	30	15,70%	14,73%	2,64%	11,70%	20,20%	12,85%	19,60%

Source: Authors' calculation.

Panel C : Difference in tested banks' capital ratios between different periods**.**

	2009 - 2011 Period (1)			**2013 Period (2)**				**2013 - 2018 Period (3)**			
	N	**Mean**	**SD**	**N**	**Mean**	**SD**	**Diff (2)-(1)**	**N**	**Mean**	**SD**	**Diff (3)-(1)**
CET 1 Ratio	142	8,93%	1,77%	50	12,19%	2,36%	3,27%***	226	13,32%	3,02%	4,39%***
Tier 1 Ratio	162	10,50%	2,19%	50	13,25%	2,56%	2,75%***	226	14,63%	3,47%	4,13%***

Source: Authors' calculation.

Appendix 3.F: Determinants of the market reaction to the disclosure of EU stress test results, employing the parsimonious model.

Each panel in this appendix reports the estimates from two distinct series of panel regressions. In each series, we regress the market reaction (to the divulgation of EU-wide stress test results) over a set of two stressed indicators and several control variables. These two series of regressions differ only in the stress test outcomes used to compute the two stressed indicators. For the series of regressions of the *baseline* scenario (*adverse* scenario), the stressed indicators are based solely on the *baseline* scenario outcomes (*adverse* scenario outcomes) estimated over a 2-year time horizon. Then, in each series, we have eight columns which present the estimates of eight distinct regressions that differ from each other only in the maturity used to calculate the market response (i.e. the dependent variable), following Agbodji *et al.* (2021) suggestions. We obtain the market reaction (at the level of all CDS maturities) by estimating the Cumulative Abnormal CDS spread Returns (CAR). We estimate it using an event study methodology over a four-day event window ((-1,+2)), the event being the stress test results' disclosure. **Panel A & B apply respectively to the 2010 and 2011 EU-wide stress tests, while Panel C applies to the 2014, 2016 and 2018 exercises**.

As stressed indicators, we have the **ΔTier1 Ratio** which is the Change in tier 1 ratio caused by the simulated scenarios, scaled by total assets. **ΔTotal Risk** is the Change in total risk exposure amount caused by the simulated scenarios, scaled by total assets. As control variables, we have the **Leverage** is the Ratio of liabilities to the sum of liabilities and equity. **Funding Stability** is the Ratio of deposits to total liabilities. **Asset Quality** is the Ratio of non-performing loans to total assets. **Liquidity** is the Ratio of net loans to deposits and short-term funding. *, **, *** indicate respectively significance at 10%, 5% and 1% levels.

Panel A: Determinants of the market reaction to the **2010 EU-wide stress test**. [*PARSIMONIOUS MODEL*]

Market reaction	CAR [-1 ; 2]															
Horizons	2-year Scenario Time Horizon															
Scenarios	**Baseline**								**Adverse**							
Maturity	6-Month	1-Year	2-Year	3-Year	4-Year	5-Year	7-Year	10-Year	6-Month	1-Year	2-Year	3-Year	4-Year	5-Year	7-Year	10-Year
Stressed Indicators																
ΔTier1 Ratio	-1.414	-1.422	-1.482	-1.264*	-1.347**	-1.258*	-1.452**	-1.415*	-1.231	-1.212	-1.193	-1.552***	-1.620***	-1.404***	-1.947***	-1.902***
	(1.053)	(1.067)	(0.953)	(0.687)	(0.620)	(0.623)	(0.684)	(0.818)	(1.066)	(1.058)	(0.985)	(0.537)	(0.469)	(0.464)	(0.513)	(0.671)
ΔTotal Risk	0.0750	0.0651	0.242	0.672**	0.975***	1.122***	1.083***	0.957**	0.188	0.200	0.287	0.666***	0.860***	0.964***	0.945***	0.870***
	(0.485)	(0.486)	(0.444)	(0.292)	(0.316)	(0.339)	(0.361)	(0.371)	(0.322)	(0.324)	(0.303)	(0.174)	(0.219)	(0.247)	(0.283)	(0.291)
Control Variables																
Leverage	-0.274	-0.283	-0.327	-0.362	-0.699	-0.829	-0.532	-0.720	-0.445	-0.437	-0.541	-0.583	-1.005**	-1.125**	-0.864*	-1.018**
	(0.827)	(0.837)	(0.798)	(0.596)	(0.531)	(0.561)	(0.510)	(0.533)	(0.770)	(0.772)	(0.746)	(0.498)	(0.448)	(0.490)	(0.435)	(0.459)
Funding Stability	-0.231*	-0.232*	-0.233*	-0.229**	-0.302***	-0.344***	-0.277***	-0.293***	-0.253*	-0.252*	-0.256*	-0.254***	-0.332***	-0.371***	-0.310***	-0.325***
	(0.131)	(0.133)	(0.127)	(0.0840)	(0.0742)	(0.0738)	(0.0630)	(0.0663)	(0.130)	(0.131)	(0.126)	(0.0767)	(0.0679)	(0.0674)	(0.0674)	(0.0726)
Asset Quality	0.826	0.855	0.819	0.547	1.212	1.459	0.914	0.700	0.654	0.711	0.611	0.337	0.928	1.191	0.589	0.406
	(0.728)	(0.756)	(0.729)	(0.637)	(0.890)	(0.996)	(0.706)	(0.604)	(0.703)	(0.719)	(0.684)	(0.547)	(0.814)	(0.936)	(0.568)	(0.485)
Liquidity	0.0752*	0.0766*	0.0817*	0.0720**	0.0508*	0.0478*	0.0482*	0.0502*	0.0898**	0.0917**	0.0968**	0.0935***	0.0734***	0.0710***	0.0742***	0.0756**
	(0.0401)	(0.0399)	(0.0402)	(0.0326)	(0.0283)	(0.0272)	(0.0274)	(0.0292)	(0.0392)	(0.0392)	(0.0389)	(0.0309)	(0.0255)	(0.0253)	(0.0260)	(0.0283)
Constant	0.163	0.168	0.212	0.270	0.627	0.761	0.464	0.644	0.293	0.281	0.383	0.433	0.869*	0.993*	0.723	0.872*
	(0.848)	(0.858)	(0.819)	(0.609)	(0.541)	(0.567)	(0.514)	(0.540)	(0.801)	(0.804)	(0.776)	(0.518)	(0.462)	(0.499)	(0.445)	(0.475)
Observations	38	37	37	38	36	38	36	38	38	37	37	38	36	38	36	38
R-squared	0.399	0.411	0.435	0.536	0.646	0.652	0.622	0.587	0.398	0.410	0.425	0.576	0.663	0.658	0.662	0.634
Adjusted R-squared	0.283	0.294	0.323	0.447	0.572	0.584	0.544	0.507	0.282	0.292	0.310	0.494	0.594	0.592	0.592	0.563
F test	0.00116	0.00113	0.000290	5.36e-05	7.51e-06	4.88e-07	9.00e-06	6.20e-06	0.000255	0.000409	0.000149	2.34e-06	7.94e-08	1.23e-08	5.36e-07	1.42e-07

Source: Authors' calculation.

Panel B: Determinants of the market reaction to the **2011 EU-wide stress test**. [*PARSIMONIOUS MODEL*]

Market reaction	CAR [-1 ; 2]															
Horizons	2-year Scenario Time Horizon															
Scenarios	**Baseline**								**Adverse**							
Maturity	6-Month	1-Year	2-Year	3-Year	4-Year	5-Year	7-Year	10-Year	6-Month	1-Year	2-Year	3-Year	4-Year	5-Year	7-Year	10-Year
Stressed Indicators																
ΔTier1 Ratio	0.566	0.519	0.702	0.722	-0.0595	-0.0658	-0.00235	-0.346	-0.316	-0.152	0.126	-0.227	-0.877	-0.861	-0.501	-0.794
	(1.679)	(1.673)	(1.692)	(1.684)	(1.682)	(1.478)	(1.318)	(1.280)	(1.195)	(1.185)	(1.192)	(1.192)	(1.032)	(0.812)	(0.843)	(0.962)
ΔTotal Risk	-0.617	-0.755	-0.699	-0.390	-0.384	0.0763	0.324	0.221	-0.839	-0.967	-0.955	-0.735	-0.884	-0.571	-0.530	-0.580
	(0.899)	(0.879)	(0.899)	(0.836)	(0.748)	(0.670)	(0.635)	(0.671)	(0.586)	(0.586)	(0.626)	(0.595)	(0.554)	(0.499)	(0.471)	(0.468)
Control Variables																
Leverage	-0.319	-0.304	-0.382	-0.302	0.280	0.643	-0.270	-0.529	-0.243	-0.0712	-0.0454	-0.258	0.0974	0.341	-0.400	-0.775
	(1.715)	(1.712)	(1.720)	(1.703)	(1.662)	(1.592)	(1.359)	(1.275)	(1.751)	(1.740)	(1.763)	(1.762)	(1.731)	(1.690)	(1.469)	(1.313)
Funding Stability	0.126	0.114	0.0961	0.110	0.105	0.0985	-0.0581	-0.0775	0.110	0.100	0.0937	0.102	0.0739	0.0780	-0.0567	-0.0926
	(0.156)	(0.154)	(0.161)	(0.161)	(0.143)	(0.136)	(0.0984)	(0.102)	(0.141)	(0.140)	(0.147)	(0.144)	(0.135)	(0.132)	(0.106)	(0.104)
Asset Quality	0.104	-0.0576	-0.215	-0.00631	0.0874	0.526	0.0372	-0.124	0.232	0.191	0.0829	0.0731	0.0280	0.346	-0.0504	-0.242
	(1.233)	(1.241)	(1.284)	(1.227)	(1.290)	(1.185)	(1.037)	(0.976)	(1.276)	(1.265)	(1.288)	(1.288)	(1.239)	(1.199)	(1.043)	(0.941)
Liquidity	-0.0167	-0.00853	-0.00635	-0.00346	0.0218	0.0320	0.0464	0.0713	-0.0250	-0.0245	-0.0280	-0.0123	0.0108	0.0252	0.0272	0.0528
	(0.0513)	(0.0520)	(0.0535)	(0.0517)	(0.0464)	(0.0448)	(0.0447)	(0.0473)	(0.0558)	(0.0553)	(0.0562)	(0.0569)	(0.0466)	(0.0473)	(0.0461)	(0.0524)
Constant	0.321	0.313	0.393	0.294	-0.269	-0.643	0.309	0.546	0.280	0.132	0.120	0.284	-0.0590	-0.330	0.467	0.815
	(1.707)	(1.704)	(1.712)	(1.696)	(1.654)	(1.580)	(1.353)	(1.273)	(1.701)	(1.690)	(1.708)	(1.712)	(1.675)	(1.641)	(1.427)	(1.281)
Observations	38	37	36	38	35	38	36	38	38	37	36	38	35	38	36	38
R-squared	0.082	0.080	0.075	0.071	0.040	0.051	0.061	0.104	0.113	0.126	0.119	0.095	0.107	0.088	0.089	0.133
Adjusted R-squared	-0.0956	-0.104	-0.116	-0.108	-0.165	-0.133	-0.133	-0.0700	-0.0587	-0.0489	-0.0632	-0.0797	-0.0841	-0.0882	-0.0990	-0.0344
F test	0.550	0.581	0.560	0.577	0.922	0.904	0.728	0.313	0.441	0.360	0.336	0.510	0.638	0.830	0.678	0.235

Source: Authors' calculation.

Panel C: Determinants of the market reactions to the 2014, 2016 and 2018 EU-wide stress tests. [*PARSIMONIOUS MODEL*]

Market reaction	CAR [-1 ; 2]															
Horizons	2-year Scenario Time Horizon															
Scenarios	**Baseline**								**Adverse**							
Maturity	6-Month	1-Year	2-Year	3-Year	4-Year	5-Year	7-Year	10-Year	6-Month	1-Year	2-Year	3-Year	4-Year	5-Year	7-Year	10-Year
Stressed Indicators																
ΔTier1 Ratio	0.385	1.260	1.562	1.509	1.257	1.179	1.100	1.307*	0.375	0.217	0.333	0.0378	-0.858	-1.300*	0.464	-0.426
	(0.979)	(0.919)	(0.959)	(0.946)	(0.877)	(0.869)	(0.790)	(0.761)	(1.172)	(1.188)	(1.098)	(1.047)	(0.750)	(0.771)	(0.832)	(0.862)
ΔTotal Risk	2.500***	2.384***	2.475***	2.166***	2.215***	1.737***	2.078***	2.018***	0.687	0.222	0.311	0.152	-0.160	-0.105	0.395	-0.0129
	(0.755)	(0.790)	(0.836)	(0.764)	(0.652)	(0.571)	(0.572)	(0.692)	(0.900)	(0.975)	(0.960)	(0.806)	(0.570)	(0.559)	(0.676)	(0.758)
Control Variables																
Leverage	1.667	2.523	2.506	1.021	0.797	-0.0335	1.080	0.803	0.697	1.286	0.648	-0.0780	-0.461	-0.323	-0.174	-0.0656
	(2.029)	(1.847)	(1.916)	(1.411)	(1.230)	(1.025)	(1.163)	(1.119)	(2.133)	(2.015)	(2.154)	(1.683)	(1.683)	(1.367)	(1.244)	(1.268)
Funding Stability	0.0487	0.137	0.134	0.105	0.365**	0.374**	0.150	0.0794	0.0174	0.121	0.143	0.100	0.255	0.278	0.183	0.0326
	(0.208)	(0.200)	(0.197)	(0.187)	(0.153)	(0.145)	(0.162)	(0.175)	(0.249)	(0.246)	(0.239)	(0.217)	(0.184)	(0.175)	(0.194)	(0.206)
Asset Quality	-1.221**	-1.092*	-1.015*	-0.842	-0.714	-0.698	-0.564	-0.884	-1.231*	-1.073	-0.942	-0.807	-0.700	-0.712	-0.389	-0.874
	(0.571)	(0.567)	(0.566)	(0.603)	(0.556)	(0.578)	(0.649)	(0.556)	(0.692)	(0.718)	(0.725)	(0.745)	(0.675)	(0.648)	(0.683)	(0.671)
Liquidity	-0.0410	-0.00725	-0.0256	-0.0401	-0.0574	-0.0646	-0.0804*	-0.0558	-0.0538	-0.0190	-0.0448	-0.0563	-0.0696	-0.0813*	-0.0908*	-0.0716
	(0.0695)	(0.0566)	(0.0540)	(0.0512)	(0.0425)	(0.0489)	(0.0478)	(0.0462)	(0.0710)	(0.0618)	(0.0595)	(0.0509)	(0.0438)	(0.0409)	(0.0515)	(0.0458)
Constant	-1.501	-2.382	-2.352	-0.948	-0.851	-0.0749	-0.996	-0.720	-0.560	-1.194	-0.586	0.107	0.377	0.229	0.179	0.128
	(1.945)	(1.761)	(1.824)	(1.340)	(1.152)	(0.949)	(1.077)	(1.054)	(2.032)	(1.908)	(2.047)	(1.587)	(1.580)	(1.279)	(1.150)	(1.183)
Observations	108	106	106	109	107	109	107	109	108	106	106	109	107	109	107	109
R-squared	0.169	0.173	0.183	0.180	0.393	0.378	0.202	0.228	0.105	0.092	0.090	0.090	0.292	0.348	0.096	0.133
Adjusted R-squared	0.119	0.123	0.134	0.132	0.356	0.342	0.154	0.183	0.0516	0.0367	0.0346	0.0361	0.249	0.309	0.0420	0.0816
F test	0.000767	0.0139	0.0211	0.0291	0.000371	1.15e-05	0.0174	0.00996	0.286	0.419	0.382	0.322	0.00310	5.51e-05	0.290	0.144

Source: Authors' calculation.

General Conclusion

The Global Financial Crisis (GFC) of 2007–2008 and the Great Recession that followed revealed major weaknesses in the supervisory and regulatory practices of banking authorities. Some of these weaknesses relate to banks' stress testing, which is a risk management tool used by banks and which is required by supervisors through the Basel II capital adequacy framework. It alerts bank management to unexpected adverse outcomes arising from a wide range of risks and provides an indication of the appropriate level of capital necessary to endure deteriorating economic conditions (Basel Committee on Banking Supervision, 2009). In order to correct shortcomings in stress testing practices employed prior to the start of the crisis, and better detect potentially fatal weaknesses of banks that may threaten the stability of the whole banking system, banking authorities formally introduce the regulatory banking stress test. It is an important scenario-based supervision tool that aims to ensure that tested banks have sufficient financial strength to absorb losses and to remain solvent and strongly capitalized, even in a difficult economic environment. While before the crisis each bank's internal stress testing program and objectives are aligned with its specific risk appetite and management, regulatory stress testing exercises are performed with common frameworks, assumptions, methodology and scenarios. In addition, at the end of each test, and for each of the scenarios implemented (usually a *baseline* and an *adverse* scenario), the outcomes are publicly disclosed by supervisors in a very detailed way, thus providing market participants with information on the financial health of tested banks, as well as their ability to absorb losses and to remain strongly solvent, even in a period of crisis.

Although several papers (mostly empirical) have studied regulatory stress tests and their informative value, this stream of the literature is still relatively new since the first stress testing exercise was carried out in 2009 (by the Federal Reserve). This thesis attempts to add to this literature by exploring a more complete and accurate analysis of the reaction of market participants following the stress test results' disclosure, including an analysis of the determinants of this reaction. It consists of three chapters that address three different issues.

The purpose of Chapter 1 is to study the main instrument used to perform our empirical investigations, namely the Credit Default Swap (CDS). To evaluate and study the informative value of regulatory stress testing exercises, we consider that it is the most appropriate instrument to use compared to stocks or bonds, given its characteristics. The recent literature has extensively used CDS, especially as a proxy of default risk since CDS spread is a relatively pure pricing of the underlying entity's default risk (Zhang *et al.*, 2009). Among the different maturities of CDS available, the literature systematically considers the (spreads of the) 5-year maturity, as it is generally considered to be the most liquid segment of the CDS market. However, very little is known about the CDS maturity that should be considered to proxy for the default risk of a bank.

Indeed, as highlighted by Ball and Cuny (2020), the term structure of a bank CDS spreads is a function of two components of market participants' uncertainty about the financial health of the bank: the uncertainty due to the imperfection of available information (first component) and the uncertainty about the occurrence of unpredictable economic shocks that will affect the bank's financial health (second component). A change in the investors' uncertainty about a bank (regardless of the component) would not have the same impact on the CDS spreads of the latter. Each maturity's spreads would be impacted differently, thus suggesting that the spreads of the different maturities do not reflect the same aspect of the default risk of the bank. As a consequence, this chapter asks: which maturity(ies) should be considered to proxy for bank default risk? Is there one or several maturities of CDS that might contain or summarize all the information available on the default risk of a bank?

To examine this question, we use a panel vector autoregressive (panel VAR) approach on a panel of 49 European banks, over the period from 2010 to 2019, at a week frequency. The objective is to determine whether there is a CDS maturity that is representative of all others, i.e. if there is a maturity of CDS whose spread variations illustrate or summarize that of all the other maturities. The results highlight that whatever the CDS maturity considered, a large part of its spread variation is explained by fluctuations in the three shortest CDS maturities (the 6-month, 1-year and 2-year maturities). Hence, the dynamics in these three CDS maturities might be useful to consider. Our findings therefore suggest that the 5-year CDS maturity may not be representative of all the others as its spread fluctuations do not reflect that of the other maturities. In fact, our empirical results do not allow us to support the existence of a maturity that is representative of all others. However, they demonstrate the existence of maturities (the 6-month, 1-year and 2-year maturities) whose dynamics might be useful to consider in order to get a general representation of the dynamics of all the maturities.

Furthermore, our results also suggest that a simultaneous shock to the two components of market participants’ uncertainty has not the same impact on CDS spreads, depending on the maturity of the CDS contract. This finding has an important implication since banking authorities, by disclosing stress test results, attempt precisely to reduce these two components of market participants' uncertainty. More precisely, in addition to improving the quality and quantity of information available on tested banks’ situation (thus reducing the first component), the disclosure of stress test results also provides valuable information on the ability of these latter to absorb losses and to remain strongly solvent (thus reducing the second component). We therefore have a simultaneous shock to the two components of market participants’ uncertainty and according to our results, this should not have the same impact on the spreads of the different maturities of CDS. This finding seriously questions the sole use of the 5-year maturity CDS spreads in the analysis of the informative value of regulatory stress tests (among others, Morgan *et al.*, 2014; Neretina *et al.*, 2014; Flannery *et al.*, 2017; Georgescu *et al.*, 2017 and Ahnert *et al.*, 2018).

As a consequence, Chapter 2 questions whether the sole use of the 5-year maturity is sufficient to entirely measure the reaction of market participants and fully evaluate the informative content of stress test results. To answer this question, we consider the ten regulatory stress tests carried out in Europe and in the US from 2009 to 2017. We evaluate and examine the reaction of market participants to the disclosure of these tests' results, employing an event study methodology and considering all maturities of CDS. Our results show that the market reaction substantially differs from one maturity to another, thus confirming our hypothesis. For a given stress test, market participants may react strongly on one maturity and weakly on another one. Our findings therefore suggest that the information disclosed impacts (reduces) the two different components of market participants’ uncertainty, and that this impact does not have the same consequence on CDS spreads, depending on the maturity of the CDS contract. Hence, we support that only using the 5-year maturity CDS spreads is not sufficient because it leads to an incomplete and partial analysis of the reaction of market participants. This, in turn, can lead to misinterpretations of the informative content of stress test results, and therefore, an incorrect appreciation of the effectiveness and informative value of regulatory stress testing exercises.

In Chapter 3, we go further by studying the determinants of the reaction of market participants following the disclosure of stress test results. Since the *baseline* and the *adverse* forward-looking scenarios (implemented during stress testing exercises) are not designed and elaborated in the same way, this chapter considers distinctly the disclosed outcomes of both in order to examine whether they explain the abnormal movements in the CDS premium, and whether their informative content is identical or not, taking into account the three time horizons of scenarios (1-year, 2-year and 3-year). Also, as these abnormal movements differ from one CDS maturity to another, is the outcomes that determine market participants' reaction different depending on the maturity of the CDS contract? To carry out our empirical investigations, we based on the 2014, 2016 and 2018 EU-wide stress tests. After estimating the market response to their results' disclosure, we regress it on participating banks' stressed indicators and several control variables. These indicators, which are computed based on the stress test outcomes, measure the impact of the two stress test scenarios on tested banks' characteristics (*Common Equity Tier 1 Ratio, Total Risk Exposure Amount, Profit & Losses, Net interest Income and Accumulated other comprehensive income*), considering each time horizon. According to our results, market participants seem to have drawn no new and relevant information on tested banks' risks and financial situation from the *adverse* scenario outcomes, at least when considering the three stress tests. Indeed, we find that the reaction of market participants is only explained by the *baseline* scenario outcomes. Furthermore, the specific information that makes market participants react is not the same from one CDS maturity to another as it differs depending on whether one considers the short-term horizon (6-month, 1-year and 2-year) which seems to be the most provided in informational content, or the medium- or long-term horizon. Going further, we evidence that even if the common equity tier 1 ratio is the most important indicator as it summarizes most factors captured by stress testing exercises, its variation (at the end of the scenarios) does not play any role in the response of market participants, unlike the variation in the remaining indicators. This may be due to the high level of tested banks' capitalization, which ensures a low risk of insolvency.

Overall, the findings of this dissertation complement the existing literature on the effectiveness and the informative value of regulatory banking stress tests (Sahin and Haan, 2016; Flannery *et al.*, 2017; Georgescu *et al.*, 2017; Ahnert *et al.*, 2018; and Sahin *et al.*, 2020, among others). They allow a better knowledge and understanding, not only of the reaction of market participants following the disclosure of stress test results, but also of the informative content of this disclosure. First of all, our results contradict the "well-known" argument according to which the 5-year CDS maturity is the most liquid segment of the CDS market (among others, Völz & Wedow, 2011; Corò *et al.*, 2013; Annaert *et al.*, 2013; Hasan *et al.*, 2014; Samaniego-Medina *et al.*, 2016; Drago *et al.*, 2017, Flannery *et al.*, 2017; Georgescu *et al.*, 2017; and Ahnert *et al.*, 2018). Over the last decade, there is almost no difference between the different segments of the CDS market in terms of liquidity, at least when considering the European CDS market. Further, our findings also suggest that a movement in each of the three shortest CDS maturities provides an insight on the (future) dynamics of the other maturities. Hence, to examine the dynamics of the spreads of CDS (for example to analyze their change following an event), considering the spreads of the three shortest CDS maturities may be more relevant and more interesting compared to the spreads of the remaining maturities, including the commonly used in the literature, the 5-year. This tends to be confirmed since this thesis brings evidence that using only the 5-year maturity CDS spreads when evaluating the reaction of market participants to the disclosure of stress test results (and the informative content of this disclosure) may lead to an incomplete and partial analysis. Following our findings, to better understand and fully appreciate the market response, and to highlight all the informative value of a stress testing exercise, we recommend to use not only the 5-year maturity CDS spreads (and/or another long-term maturity), but also the CDS spreads of at least one of the short-term maturities (6-month, 1-year, 2-year and 3-year maturities). Finally, our findings may have important policy implications for banking supervisors since we shed some light on the precise stress test scenarios and outcomes that influence market participants, depending on the time horizon and the test period (crisis or tranquil period). It may also help researchers to better examine the informative content of stress tests' disclosed outcomes and better understand the market response and the factors driving it. Also, stress tests are primarily focused on the assessment of the impact of risk drivers on the solvency of tested banks. However, according to our findings, the change in common equity tier 1 ratio does not always influence market participants. This may have some implications for banking supervisors in the design of the methodology and the scenarios of future stress testing exercises.

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A B S T R A C T

The aim of this thesis is to contribute to the current debate on the informative value of regulatory banking stress tests by exploring a more complete and refined analysis of the informative content of their disclosed outcomes. As regulatory stress tests provide information on the ability of tested banks to absorb losses and remain strongly solvent (thus avoiding default), to examine whether this information is new and relevant for market participants and evaluate their reaction, an appropriate instrument to use is Credit Default Swaps (CDSs). Indeed, CDS spread is a relatively pure pricing of bank default risk (Zhang *et al.*, 2009), over different maturities. **Chapter 1** therefore analyzes CDS instruments by mainly asking: which maturity(ies) should be considered to proxy for bank default risk? In an attempt to answer this question, this chapter investigates if there is a maturity of CDS whose spread variations illustrate or summarize that of all the other maturities. Our results suggest that the dynamics in the three shortest CDS maturities (the 6-month, 1-year, and 2-year maturities) might be useful to consider to get a general representation of the dynamics of all the maturities. Moreover, our investigations suggest that the disclosure of stress test results should be informative for all maturities of CDS and should impact their spreads differently. As a result, **Chapter 2** questions whether the sole use of the 5-year maturity CDS spreads is sufficient to appreciate the reaction of market participants to the disclosure, and to fully evaluate the informative content of this disclosure. The results show that it is not sufficient. Market participants react differently depending on the maturity of the CDS contract. Hence, we support that only considering the 5-year maturity CDS contracts may lead to an incomplete and partial analysis of the reaction of market participants. This, in turn, can lead to misinterpretations of the informative content of stress test results. **Chapter 3** then goes further by studying the determinants of market participants' reaction considering distinctly the disclosed outcomes of the two scenarios implemented, namely the *baseline* and the *adverse* scenarios. The aim is to examine whether both outcomes explain the abnormal movements in tested banks' CDS spreads considering all maturities, and whether their informative content is identical or not. We find that in times of panic, market participants seem to derive new and relevant information from both scenarios' outcomes (especially the *adverse* ones). But, in times of calm, only the *baseline* scenario outcomes seem to provide them with such information; moreover, we show that this information mainly concerns market participants who have a short-term investment horizon.

Keywords | Credit Default Swap, CDS Maturity, CDS Spreads, Panel VAR, Granger-Causality, FEVD, Regulatory Stress Test, Information, Market Reaction, Event Study, Scenario, Time Horizon.

R É S U M É

Cette thèse a pour objectif de contribuer à la littérature sur les tests de résistance réglementaires (stress tests) des banques en menant une étude plus complète et plus affinée du contenu informatif des résultats divulgués des tests. Étant donné que les stress tests fournissent aux marchés des informations sur la capacité des banques testées à absorber des pertes et à rester solidement solvables (évitant ainsi le défaut), pour examiner si ces informations sont nouvelles et pertinentes pour les acteurs du marché et évaluer la réaction de ces derniers, un instrument approprié à utiliser est le Credit Default Swaps (CDSs). En effet, la prime de CDS est une tarification relativement pure du risque de défaut bancaire (Zhang *et al.*, 2009), sur différentes échéances (maturités). Le **chapitre 1** analyse donc les instruments de CDS en posant essentiellement la question : quelle(s) maturité(s) doit-on considérer lorsqu'on veut utiliser le spread (ou prime) de CDS comme proxy du risque de défaut bancaire ? Pour tenter de répondre à cette question, ce chapitre examine s'il existe une ou plusieurs maturités de CDS dont les variations de spreads illustrent ou résument celles de toutes les autres maturités. Nos résultats suggèrent que la dynamique des trois plus courtes maturités de CDS (les maturités de 6 mois, 1 an et 2 ans) pourrait être utile à considérer si on veut avoir une représentation générale de la dynamique de toutes les maturités. De plus, nos investigations suggèrent que la publication des résultats des stress tests devrait être informative pour toutes les maturités des CDS et devrait impacter leurs spreads différemment. Dès lors, le **chapitre 2** s'interroge si la seule utilisation des spreads de CDS de maturité 5 ans est suffisante pour apprécier la réaction des acteurs du marché à la suite de la publication des résultats, et évaluer pleinement le contenu informatif de cette publication. Les résultats montrent que ce n'est pas suffisant, car les acteurs du marché réagissent différemment en fonction de la maturité du contrat de CDS. Par conséquent, la seule prise en compte de la maturité de 5 ans peut conduire à une analyse incomplète et partielle de la réaction des acteurs du marché. Ceci, à son tour, peut conduire à des interprétations erronées du contenu informatif des résultats des stress tests. Le **chapitre 3** propose d'aller plus loin en étudiant les déterminants de la réaction des acteurs du marché suite à la publication, considérant distinctement les résultats divulgués des deux scénarios mis en œuvre, à savoir le scénario de *base* et le scénario *défavorable*. L'objectif est d'examiner si les résultats issus des deux scénarios expliquent les mouvements anormaux des spreads de CDS des banques testées (considérant toutes les maturités), et si leur contenu informatif est identique ou non. Nos résultats montrent qu'en période de panique, les acteurs du marché semblent tirer des informations nouvelles et pertinentes des résultats des deux scénarios (en particulier du scénario *défavorable*). Mais, en période d'accalmie, seuls les résultats du scénario de *base* semblent leur fournir de telles informations ; de plus, nous montrons que ces informations concernent principalement les acteurs du marché qui ont un horizon d'investissement à court terme.

Mots clés | Credit Default Swap (CDS), Maturité de CDS, Spread de CDS (ou Prime de CDS), Autorégression Vectorielle, Causalité au Sens de Granger, FEVD, Tests de Résistance Réglementaires, Information, Réaction du Marché, Étude d'événement, Scénario, Horizon Temporel.