Sovereign and bank risk: Contagion, policy uncertainty and interest rates

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Abstract

This dissertation addresses the dependence between sovereign and bank default risk and the importance of (policy) uncertainty and interest rates for this nexus. To this end, the thesis includes four self-contained but interrelated studies with different methodological approaches. The first paper sheds light on the cross-country contagion of sovereign and bank default risk between 2009 and 2021 to assess the introduction of the European Banking Union in 2014. The study utilizes a combination of vector autoregressive, network, and wavelet methods to derive directed and dependence-weighted contagion networks across various time horizons. Based on Credit Default Swap premia of systemically important banks in the 10 largest eurozone countries, the estimated network structures provide evidence that the introduction of the Single Supervisory Mechanism, as part of the European Banking Union, has been effective in reducing overall financial contagion in the short run (up to 1 month). In the long run, the risk dependence is still very pronounced. Nevertheless, a shock in sovereign or bank risk is less severely transmitted to other eurozone countries after 2014, indicated by lower volatility spillovers. Thus, the Banking Union supports financial stability by weakening the strength of dependence rather than eliminating the dependence itself. The second study takes a closer look at the domestic dependence between sovereign and bank risk in 14 countries. The estimation of dynamic conditional correlations indicates that the dependence is significantly higher in euro member states. This reveals a systematic eurozone risk factor mainly rooted in the "home bias" of domestic sovereign bond holdings of eurozone banks. To address this bias, the European Union should explicitly introduce disincentives against highly concentrated sovereign exposures. Moreover, fixed-effect panel regressions indicate that the sovereign-bank correlation increases in times of great policy uncertainty, high interbank market rates, low bank lending margins, and a low ratio of core bank capital. Economically, banks with a low level of core equity capital are less capable of withstanding shocks to their balance sheets, which spills over to the state and results in higher risk dependence. In addition, banks charge each other higher rates for unsecured short-term lending during times of financial distress. In this way, bank liquidity issues and lending aversion in the interbank market are passed on to other banks and ultimately to the sovereign. Overall, the second study emphasizes the importance of bank capital adequacy regulations and joint European policies to mitigate domestic sovereign-bank dependencies. The third study extends prior results and examines the impact of economic policy uncertainty (EPU) on the sovereign-bank nexus by introducing a continuous wavelet time domain. This setting allows to derive causal "lead-

lag relationships" for each point in time. The assessment of the lead-lag relationships in 10 countries shows that a higher level of sovereign default risk leads to an increase in bank risk in the short horizon. In the medium run (6–32 months), the relationship reverses and the default risk of banks determines sovereign risk. Moreover, the wavelet coherency, as a measure of correlation, indicates significant contagion in times of political turbulence and uncertain election outcomes. Once the influence of policy uncertainty on sovereign and bank risk is eliminated, the partial coherency shows that the sovereign-bank dependence significantly weakens. This reveals the great relevance of political risk factors for the sovereign-bank nexus. The final study addresses the impact of different sources of uncertainty. Besides newspaper-based economic policy uncertainty, the study employs the implied volatility of options written on the S&P500 and a Twitter-based uncertainty index. Based on stock returns of the 22 largest U.S. banks, the computation of principal components, Granger causality, and volatility spillover provides evidence that EPU and Twitter-based uncertainty capture different sources of investor perception in the very short horizon (up to 1 week). Although both measures are positively correlated, a higher level of Twitter uncertainty reduces bank returns in the short run, while newspaper-based uncertainty becomes relevant in the medium run. Hence, Twitter captures consumer uncertainty more appropriately in the short term than newspapers, which usually have a delay in responding to news due to editorial processes. Financial market uncertainty is the most important factor. In addition, the study considers information about individual bank asset allocations to examine if these characteristics alter the impact of uncertainty on bank returns. The findings reveal that the impact of uncertainty is considerably stronger for banks with a high ratio of loans to total assets and large off-balance-sheet activities, measured by the ratio of derivatives to total bank assets. Although credit derivatives are important for securitizing and hedging credit risk, the results show that derivatives may also destabilize banks in terms of a higher uncertainty exposure. Moreover, banks with a greater loan ratio face a higher level of credit risk. Assuming that bank risk can be transmitted to the state through the sovereign-bank nexus, the results emphasize the importance of differentiating between the sources of uncertainty to evaluate its implications for financial stability. The findings also highlight the increasing importance of social media for the financial markets.

Kurzfassung

Diese Dissertation befasst sich mit der Abhängigkeit der Ausfallrisiken von Staaten und Banken sowie der Bedeutung von (politischer) Unsicherheit und Zinssätzen für diesen Nexus. Zu diesem Zweck umfasst die Arbeit vier in sich geschlossene, jedoch inhaltlich miteinander verbundene Studien mit verschiedenen methodischen Ansätzen. Die erste Studie modelliert länderübergreifende Abhängigkeiten zwischen Staaten und Banken im Zeitraum von 2009 bis 2021, um die Einführung der Europäischen Bankenunion im Jahr 2014 zu bewerten. Die Arbeit kombiniert vektorautoregressive- und Netzwerkmethoden mit Wavelet-Transformation, um kausale und gewichtete Ausfallrisiko-Netzwerke über verschiedene Zeithorizonte abzuleiten. Basierend auf Kreditausfall-Swap Prämien systemrelevanter Banken der 10 größten Euro-Mitgliedsstaaten zeigen die modellierten Netzwerkstrukturen, dass die Einführung des einheitlichen Aufsichtsmechanismus (SSM) als Teil der Bankenunion die Abhängigkeiten in der kurzen Frist (bis 1 Monat) deutlich verringert hat. Langfristig ist die Risikoabhängigkeit jedoch recht beständig. Dennoch wird ein Schock im Staats- oder Bankenausfallrisiko nach 2014 weniger stark auf andere Länder der Eurozone übertragen, was sich in geringeren Volatilitätsspillover-Effekten widerspiegelt. Entsprechend unterstützt die Bankenunion die Finanzstabilität, indem sie die Stärke der Abhängigkeit abschwächt, anstatt die Abhängigkeit selbst zu beseitigen. Die zweite Studie thematisiert die inländische Abhängigkeit zwischen Staaten und Banken in 14 Ländern. Die Berechnung dynamischer Korrelationen zeigt, dass die Abhängigkeit in Ländern der Eurozone deutlich höher ist. Dies offenbart einen systematischen Risikofaktor in der Eurozone, der hauptsächlich in der „Heimatverbundenheit“ inländischer Banken begründet ist. Dementsprechend sollte die Europäische Union Anreize gegen eine hohe Konzentration inländischer Staatsanleihen-Bestände in Bankbilanzen einführen. Darüber hinaus zeigen Panel-Regressionen, dass die Korrelation zwischen Staaten und Banken in Zeiten großer politischer Unsicherheit, hoher Interbankmarktzinsen, niedriger Kreditmargen und einer niedrigen Kernkapitalquote der Banken signifikant zunimmt. Banken mit einem niedrigen Kernkapitalanteil können Schocks in ihren Bilanzen weniger gut abfedern, was sich auf den Staat übertragen und zu einer höheren Risikoabhängigkeit führen kann. Darüber hinaus verlangen Banken in ökonomisch unsicheren Zeiten voneinander höhere Zinsen für ungesicherte kurzfristige Kredite. Auf diese Weise werden Liquiditätsprobleme über den Interbankenmarkt an andere Banken und letztlich an den Staat weitergegeben. Somit untermauert die zweite Studie die Bedeutung von Eigenkapitalvorschriften und einer gemeinsamen europäischen Politik zur Abschwächung des Staat-Banken Nexus. Die dritte

Studie baut auf vorherige Ergebnisse auf, indem die Auswirkung von wirtschaftspolitischer Unsicherheit auf den Staat-Banken Nexus genauer betrachtet wird. Die Anwendung kontinuierlicher Wavelet Methoden ermöglicht die Ableitung von kausalen „Lead-Lag-Beziehungen“ für jeden Zeitpunkt. Die Analyse der Lead-Lag-Beziehungen in 10 Ländern zeigt, dass ein höheres Ausfallrisiko von Staaten kurzfristig zu einem Anstieg des Bankenausfallrisikos führt. Mittelfristig (6–32 Monate) kehrt sich die Beziehung um und ein höheres Ausfallrisiko von Banken erhöht das Staatsausfallrisiko. Zudem zeigt die Wavelet-Kohärenz als ein Maß der Abhängigkeit erhebliche Spillover-Effekte in Zeiten politischer Turbulenzen und unsicherer Wahlausgänge. Wenn der Einfluss der politischen Unsicherheit auf das Staats- und Bankenausfallrisiko eliminiert wird, zeigt die partielle Wavelet-Kohärenz, dass die Abhängigkeit signifikant abnimmt. Dies belegt die große Bedeutung politischer Risikofaktoren für den Staat-Banken Nexus. Die letzte Studie befasst sich mit den Auswirkungen verschiedener Quellen von Unsicherheit. Neben zeitungsbasierter Unsicherheit betrachtet die Studie die implizite Volatilität von Optionen auf den S&P500 und einen Twitter-basierten Unsicherheitsindex. Basierend auf Aktienrenditen der 22 größten US-Banken zeigen die Berechnung von Hauptkomponenten, Granger-Kausalität und Volatilität-Spillover, dass zeitungsbasierte und Twitter-basierte Unsicherheit die Anlegerwahrnehmung auf sehr kurze Sicht (bis 1 Woche) unterschiedlich abbilden. Obwohl beide Messgrößen positiv korreliert sind, reduziert eine höhere Twitter-basierte Unsicherheit die Bankrenditen in der kurzen Frist, während zeitungsbasierte Unsicherheit mittelfristig von Relevanz ist. Dies lässt sich darin begründen, dass Twitter die Unsicherheit der Verbraucher kurzfristig besser abbildet, da Zeitungen aufgrund redaktioneller Abläufe erst mit Verzögerung auf Nachrichten reagieren können. Die Finanzmarktunsicherheit ist der bedeutendste Faktor. Darüber hinaus stützt sich die Studie auf Informationen über die Vermögensallokationen der Banken, um deren Bedeutung für den Zusammenhang zu beurteilen. Die Ergebnisse zeigen, dass der Einfluss von Unsicherheit bei Banken mit einem hohen Anteil an Krediten und großen außerbilanziellen Aktivitäten, gemessen am Anteil der Derivate, deutlich stärker ist. Obwohl Kreditderivate für die Verbriefung und Absicherung von Kreditrisiken wichtig sind, zeigen die Ergebnisse, dass Derivate auch destabilisierend wirken können, da Banken anfälliger für erhöhte Unsicherheit sind. Zudem tragen Banken mit einem höheren Kreditverhältnis ein höheres Maß an Kreditrisiken. Unter der Annahme, dass sich Bankenrisiken auf Staaten übertragen können, unterstreichen die Ergebnisse die Bedeutung zwischen den Quellen der Unsicherheit zu differenzieren, um deren Auswirkungen auf die Finanzstabilität zu bewerten. Zudem verdeutlichen die Ergebnisse die Bedeutung sozialer Medien für die Finanzmärkte.

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Chapter 1

Overall introduction

"Our challenge in the euro area is to ensure that, when banks fail and the public sector has to intervene, it does not result in a recurrence of the bank-sovereign nexus"

Draghi (2014)

Establishing and maintaining financial stability is a fundamental aspect of a functioning financial system. The 2008 financial and subsequent European debt crisis put the political and economic survivability of the eurozone to the test and revealed the existence of dangerous risk dependencies across the entire system (Böhm and Eichler, 2020). In particular, commercial banks heavily invested in domestic sovereign debt to earn the entire risk premium, while the risk itself was mainly borne by their creditors (Andreeva and Vlassopoulos, 2019). These incentives led to a "home bias" in bank bond holdings, which is blamed as one of the main reasons for the escalation of the eurozone crisis (Brunnermeier et al., 2016). Caused by large-scale financial sector bailouts, the sovereign creditworthiness declined, which, in return, eroded the value of guarantees in bank balance sheets. This ultimately increased bank funding costs and impaired their ability to supply credits, which hampered the economic recovery after the crisis (Fratzscher and Rieth, 2015; Acharya et al., 2014). In the literature, this two-way interdependence between the default risk of governments and banks is called the "sovereign-bank nexus".

To effectively achieve financial stability, the close link between governments and the financial sector needs to be broken. In the aftermath of the crisis, the introduction of government guarantee schemes aimed at reducing the risk premia on bank liabilities and migrating sovereign-bank dependencies (Angelini et al., 2014). In addition, the European Banking Union (EBU) has been established in 2014 to restore stability in the banking sector (Houben and Vandenbruwaene, 2017). However, the developments between 2014 and 2022 have revealed the persistence of the home bias and the presence of significant risk transmissions between financial intermediaries and states. Following the economic downturn triggered by the COVID-19 pandemic, eurozone banks were seeking save investments by heavily investing in domestic sovereign debt securities. During the first months of the pandemic, eurozone banks increased their holdings of domestic government bonds by roughly 10%. This constitutes the largest growth in three consecutive months ever recorded.[1] Second, a series of political events highlighted the importance of policy uncertainty as a systematic risk factor. For instance, the sharp decrease in government bond prices after the Italian general election in March 2018 put the markets in fear and endangered the stability of the banking system through substantial risk transmissions to other eurozone members. Similar market responses are observed after the Brexit referendum in 2016, the non-confidence vote against Spain's prime minister in 2018, and the 2016 presidential election in the United States. Drawing from these events, several studies argue that economic policy uncertainty (EPU) has become an important risk factor for banks and the financial system as a whole (Berger et al., 2022; Stolbov and Shchepeleva, 2020; Naifar et al., 2018; Bordo et al., 2016). Third, the development of (negative deposit) interest rates between 2014 and mid-2021 hindered the ability of eurozone banks to strengthen their balance sheets and to generate organic capital growth (Molyneux et al., 2019). Assuming that bank risk can be transmitted to sovereign risk and vice versa, this implies a potential impact on the sovereign-bank nexus. Fourth, attention must be given to the sharp rise in the influence of social media, which may also affect banking sector risk. Aharon et al. (2022) and Baker et al. (2021) claim that Twitter has become a "new-era newspaper", which represents the beliefs of a large cross-section of social media users. As Twitter is used as an information source for retail investors nowadays, tweets can have a significant impact on trading behavior and financial markets. Not least the case of GameStop has set an example of how retail investors can boost the stock price and cause short-selling hedge funds to suffer significant losses (Umar et al., 2021).

To address the aforementioned points, this dissertation comprises four self-contained yet related studies, which shed light on the main characteristics of sovereign-bank risk contagion and the potential influence of policy uncertainty, interest rates, and social media on this nexus.[2] To this end, each chapter implements a different methodological setting to measure financial contagion. This approach combines the informational advantages of different methods and ensures robust results in the context of this thesis. Hence, each

[1] European Central Bank (2022) - Government Finance Statistics.

[2] Note: As this dissertation contains studies written and published during different stages of my personal development during my doctorate, the writing style may differ across the chapters of this thesis.

chapter serves as a robustness check for the others. According to Dornbusch et al. (2000) and Forbes and Rigobon (2002), financial contagion is described as periods with a significant increase in (cross-market) correlation.

Chapter 2, titled *"Sovereign and bank dependence in the eurozone: A multi-scale approach using wavelet-network analysis"*, utilizes network statistics to measure overall financial contagion of sovereign and bank default risk and to assess the introduction of the European Banking Union in 2014. Based on daily Credit Default Swap (CDS) premia of systemically important eurozone banks in 10 countries between 2009 and 2021, the study combines vector autoregressive, network, and wavelet methods to establish directed and dependence-weighted risk networks for different time horizons. The application of wavelet tools challenges the boundaries of traditional econometric methods by considering the frequency structure of contagion.[3] If policymakers have a better understanding of how financial shocks are transmitted in the short, medium, and long run, they could react more effectively to minimize potential damage to the economy. The estimated network structures provide evidence that the introduction of the Single Supervisory Mechanism, as part of the EBU, has been effective in reducing sovereign-bank contagion in the short run (up to 1 month). However, it is less effective in the long run, as sovereigns and banks are indirectly and fundamentally linked through the domestic economy. Nevertheless, a shock in sovereign or bank risk is less severely transmitted to other eurozone members after 2014, indicated by lower volatility spillovers. The COVID-19 pandemic as a "real-life stress test" confirms these findings, as the strength of default risk spillovers remained low over 2020–2021, while the network connectivity increased. Overall, the study demonstrates that the European Banking Union effectively supports financial stability by weakening the strength of dependence rather than eliminating the dependence itself.

Chapter 3, titled *"Policy uncertainty, interest rate environment and the dynamic correlation between sovereign and bank default risk"*, addresses the domestic sovereign-bank nexus by estimating dynamic conditional correlations between sovereign and (joint) banking sector risk in a country. Based on a sample of 25 eurozone and 23 non-eurozone banks in 14 countries, the study demonstrates that the correlation is considerably higher in euro member states. This reveals a systematic eurozone risk factor, which roots in the sovereign bond home bias of eurozone banks. Using fixed effects panel regression, the study iden-

[3] Wavelet methods ordinate from the field of electrical engineering, where they are applied to analyze local signals. Due to their advantages, wavelets have been applied in several other areas. However, the application to the field of economics and finance is relatively recent (Hkiri et al., 2016).

tifies potential drivers of the sovereign-bank correlation: The nexus increases in times of great policy uncertainty, high interbank market rates, low bank lending margins, and a low ratio of core bank capital relative to total risk-weighted assets. From an economic perspective, banks with a low level of core equity capital are less capable of withstanding adverse shocks to their balance sheets. These risks are passed on to the state, which results in a higher correlation. Moreover, banks charge each other higher rates for unsecured short-term lending in times of financial distress. The regression results indicate that these bank liquidity issues and lending aversion in the interbank market are passed on to other domestic banks and the sovereign. The findings are robust against different specifications and a series of macroeconomic and financial control variables. Overall, the study demonstrates the importance of bank capital adequacy regulations and joint European policies to mitigate domestic sovereign-bank dependencies.

Chapter 4, titled *"Policy uncertainty and the sovereign-bank nexus: A time-frequency analysis using wavelet transformation"*, builds on Chapter 3 by taking a closer look at the impact of policy uncertainty on the sovereign-bank nexus with the use of continuous wavelet tools. While the discrete specification applied in Chapter 2 decomposes a time series into a finite number of levels, continuous wavelets yield a subtler resolution and provide a toolkit for assessing time-varying causality for every single point in time. Based on 32 banks in 10 countries, the study estimates risk-adjusted CDS premia to capture the fundamental co-movement between sovereign and bank risk that goes beyond what can be attributed to movements in the financial markets. The use of unadjusted CDS spreads could be misleading, as periods of high market volatility usually increase the co-movement. The computation of wavelet coherency and "lead-lag relationships" as measures of causal dependence reveals two interesting results. First, a higher level of sovereign default risk leads to an increase in bank default risk in the short run. In the medium horizon (6–32 months), the causality reverses and bank default risk impacts sovereign risk. This indicates a bidirectional nexus between sovereign and bank risk that evolves over different time horizons. Second, the sovereign-bank dependence significantly tightens in times of political turbulence, such as after the Italian parliament election in 2018 or the Brexit referendum in 2016. Once the influence of policy uncertainty on sovereign and bank risk is eliminated, the partial coherency indicates that the dependence considerably weakens. The patterns are statistically significant at a 5% level. This emphasizes the great relevance of political risk factors for the sovereign-bank nexus.

Chapter 5, titled *"Does the source of uncertainty matter? The impact of financial, newspaper and Twitter-based measures on U.S. banks"*, examines the influence of different sources of uncertainty on (non-idiosyncratic) bank stock returns in the United States.[4] In addition to newspaper-based EPU employed in Chapter 3 and Chapter 4, the study considers financial market implied volatility (VIX) and daily Twitter-based economic uncertainty (TEU) of Baker et al. (2021). Based on stock returns of the 22 largest U.S. banks, the computation of principal components, Granger causality, and volatility spillover shows that EPU and Twitter-based uncertainty capture different aspects of investor perception in the very short horizon (up to 1 week). Although both measures co-move, a higher level of Twitter uncertainty negatively affects bank returns in the short run, while newspaper-based EPU is a relevant risk factor in the medium run. Intuitively, Twitter captures consumer uncertainty better in the short term than newspapers, which usually have a delay in responding to news due to editorial processes. Hence, Twitter-based information gets integrated into bank stock prices more quickly. Financial market uncertainty is the most important risk factor for banks. In addition, the study considers the individual bank asset allocations to infer if these characteristics alter the impact of uncertainty on bank returns. The results demonstrate that the impact of uncertainty is considerably stronger for banks with a high ratio of loans to total assets and large off-balance-sheet activities, measured by the ratio of derivatives to total bank assets. Although credit derivatives are important for securitizing and hedging credit risk, the results show that derivatives may also destabilize banks in terms of a higher uncertainty exposure. Moreover, banks with a greater loan ratio likely face a higher level of credit risk, thereby altering the elasticity to uncertainty shocks. Finally, banks exhibited greater sensitivity to uncertainty during the COVID-19 pandemic. Assuming that bank risk can be transmitted to the sovereign via the sovereign-bank nexus, the results emphasize the importance of differentiating between the source of uncertainty to evaluate its implication for financial stability. The findings also highlight the increasing importance of social media platforms like Twitter for the financial markets.

Chapter 6 draws an overall conclusion by summarizing the main results of each chapter and pointing out the implications derived in this dissertation.

[4]The study considers the U.S. market since the Twitter- and newspaper-based uncertainty measures are available on a daily rather than a monthly frequency. Since Twitter information is quickly priced by the stock market, the use of daily data is crucial in the context of the research question. Moreover, stock prices are used to increase the bank sample size and to overcome issues caused by illiquid CDS premia.

Chapter 2

Sovereign and bank dependence in the eurozone: A multi-scale approach using wavelet-network analysis

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Abstract

This study establishes time-frequency networks of sovereign and bank contagion in the eurozone over the period 2009–2021. By applying discrete wavelet transformation, daily CDS premia of sovereigns and systemically important banks are decomposed into multi-horizon components to specify directed and dependence-weighted networks. Dynamic analysis shows that the network connectivity and the strength of the dependencies are significantly lower after the introduction of the European Banking Union in 2014. While the strength effect is pronounced across all time horizons, the network connectivity only reduces in the short and medium run. This provides evidence that the new regulatory framework promotes financial stability but is more effective in the short and medium horizons. The consideration of the COVID-19 pandemic as a "real-life stress test" confirms these findings, as the strength of the dependencies keeps at significantly lower levels.

Keywords: Sovereign-bank contagion, financial stability, network analysis, wavelets.

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2.1 Introduction and related literature

Connections between sovereign and banking sector risk are important for financial and economic stability. In the course of the global financial crisis, financial sector risks were passed on to sovereign states, who explicitly or implicitly guaranteed large portions of bank liabilities. This, in return, provoked the debt problems of multiple sovereigns in the eurozone, causing the financial crisis to turn into a full sovereign debt crisis (Kalbaska and Gątkowski, 2012). In recent years, a significant body of literature focused on analyzing the joint dynamics between sovereigns and banks, showing that banks are heavily invested in domestic sovereign debt securities. This “home bias” occurs for a variety of reasons, not least because of regulatory incentives in terms of lower liquidity and capital requirements (Fiordelisi et al., 2020). In addition, bond holdings are important to access central bank liquidity and to collateralize interbank market operations. However, higher exposure to the domestic state makes banking sector assets sensitive to the government health. A loss in market confidence of government creditability affects the balance sheets of domestic banks, reduces banks’ ratings, and pushes up their funding costs (Acharya et al., 2014; Alter and Beyer, 2014). This, again, leads to further deterioration of sovereign creditworthiness, which amplifies the risk dependence. Relating to the European debt crisis, Erce (2015), Garcia de Andoain and Kremer (2017), and Bratis et al. (2018) show that a bank bailout led to a significant increase in sovereign credit risk. This dependence is more pronounced in countries with a large level of public debt and higher sovereign exposure of domestic banks. Fratzscher and Rieth (2015), moreover, blame the two-way relation to have aggravated and deepened the recession after the crisis.

Following Gomez-Puig et al. (2019), Figure 2.1 illustrates direct and indirect connections between sovereigns and banks of two countries A and B. Apart from the home bias, individual banks hold claims against each other. These holdings are guaranteed by public or private deposit insurance corporations in most countries (Gomez-Puig et al., 2019). In this way, contagion risks can be transmitted within the banking sector due to common credit exposure, derivatives trades, and interbank lending (Alter and Beyer, 2014). In general, banks are internationally connected through cross-border financial flows. Taking into account persisting domestic sovereign-bank relations, a complex system of contagion exists. Breckenfelder and Schwaab (2018) demonstrate that banking sector risk in stressed countries affects the credit risk of non-stressed sovereigns. This issue is especially pronounced in the euro area, as default risks are interconnected through risk-sharing mechanisms, such as the European Stability Mechanism (ESM) or the common central

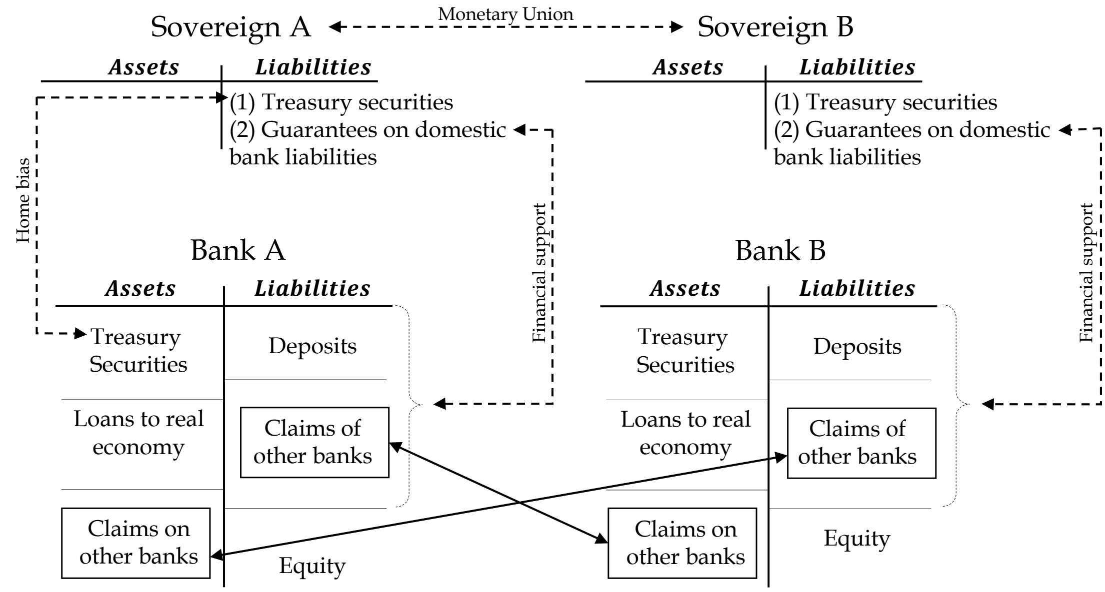

Figure 2.1: Connections between sovereign and bank risk

bank policy. Accordingly, Gori (2021) investigates the nexus between banks' foreign assets and sovereign default risk in developed economies. He finds that banks' foreign exposure is an important determinant of sovereign default probability. Zhu (2018) examines the transmission of sovereign, banking, and corporate default risks among eurozone countries between 2008 and 2013. He indicates that a significant proportion of sovereign and bank default risk variation is explained by foreign shocks. In addition, heavy indirect linkages exist through the domestic economy. Some studies highlight that the economy is likely to suffer from poorer public services, higher taxation, increasing cost of capital, and deterioration of bank asset quality if sovereign risk increases (Altavilla et al., 2017; Angelini et al., 2014). Finally, Buchholz and Tonzer (2016) show that sovereign markets in the eurozone are strongly interconnected and exhibit much higher default risk co-movements than non-eurozone countries. They, furthermore, reveal that lower liquidity, higher risk aversion, and lower sentiment in financial markets are associated with higher correlations of sovereign default risks across countries. Overall, the literature emphasizes the close connection between the financial health of banks and sovereigns in the euro area. In the aftermath of the sovereign debt crisis, the European Union has implemented a set of measures to restore stability in the banking sector. These measures include asset relief interventions, recapitalizations, and liquidity indicators other than guarantees (Fiordelisi et al., 2020). The most ambitious one was the introduction of the European Banking Union (EBU) in 2014. The EBU consists of three pillars: The Single Supervision Mechanism (SSM), the Single Resolution Mechanism (SRM), and the common Deposit Guarantee Scheme (DGS). Among these pillars, the SSM was the first to become operational on November 4, 2014 (Sáiz et al., 2019). The new framework unifies supervision to limit the fragmentation of markets in Europe and to reduce contagion between sovereigns and banks. While the European Central Bank (ECB) is responsible for supervising systemically important credit institutions, national authorities remain the competent supervisors for the other institutions (Houben and Vandenbruwaene, 2017). The SSM also enables the direct intervention of the European Stability Mechanism to provide financial assistance to troubled banks. The second pillar was introduced on August 19, 2014, and entered fully into force on January 1, 2016. The Single Resolution Mechanism applies to all banks that are supervised by the ECB. The mechanism aims to ensure an orderly resolution of failing banks to minimize the impact on the real economy (Houben and Vandenbruwaene, 2017). Overall, stricter regulation and tougher supervision should improve the risk profile of banks and enhance the robustness of the eurozone banking system. The third pillar has not yet been implemented due to ongoing negotiations and moral hazard concerns about a common deposit insurance scheme (Fernández-Aguado et al., 2022).

The effectiveness of the new regulatory framework on financial stability is evaluated by a few studies. Covi and Eydam (2020) use a panel of daily Credit Default Swaps (CDS) to evaluate the implementation of the European Banking Union. They indicate considerable sovereign-bank contagion between 2012 and 2014. Nevertheless, the spillovers are statistically insignificant after the implementation of the EBU and the magnitude of the dependence is generally lower. Sáiz et al. (2019) focus on the announcement of the Single Supervision Mechanism in March 2013. They demonstrate that the announcement had an immediate effect on CDS spreads by reducing contagion between banks and sovereigns. In addition, Fiordelisi et al. (2020) show that the introduction of the SRM significantly reduced the credit risk connectedness of sovereigns and banks in the eurozone. However, a most recent study by Soenen and Vennet (2021) reveals that sovereign-bank contagion persists over the 2015–2019 period. The empirical research indicates that sovereign default risk is transmitted to bank risk with an amplification factor. In accordance, Breckenfelder and Schwaab (2018) argue that the Security Supervision Mechanism not only promotes financial stability but also acts as a channel for financial contagion. They demonstrate that non-stressed sovereigns take on the banking sector risk from stressed countries as a response to the announcement of the first comprehensive assessment results in the context of the SSM. Looking at the most recent developments, the COVID-19 pandemic can be perceived as a "real-life stress test" of the EBU implementation. Existing literature shows that the pandemic increased systemic risk in the eurozone banking sector, whereby the adverse effects are more pronounced for large and highly leveraged banks (Duan et al., 2021). Acharya et al. (2021) and Dunbar (2021), furthermore, show a significant underperformance of bank stock returns relative to other firms, which they attribute to high degrees of balance-sheet liquidity risk. Çolak and Öztekin (2021) demonstrate that bank lending is reduced in countries that are heavily affected by the pandemic. In addition, sovereign default risk significantly increased across all eurozone countries.

Overall, there is no complete consensus about the effect of the European Banking Union on financial stability. This may demand the introduction of a new dimension, the time-frequency space. If policymakers have a better understanding of how financial shocks are transmitted across different frequencies (short, medium, long run), they could react more effectively to minimize potential damage. Hence, understanding the network structure through which the initial shocks are transmitted is very valuable (Bostanci and Yılmaz, 2020). One of the limitations in the past literature is the use of traditional econometric methods, which do not capture time and frequency information simultaneously (Gupta et al., 2018). Wavelet-based methods are superior, as they overcome these limitations (Reboredo and Rivera-Castro, 2013). The empirical methodology of this paper contains three main steps. First, Maximum Overlap Discrete Wavelet Transformation (MODWT) is applied to decompose sovereign and bank CDS into multi-horizon components. Second, contagion relationships are derived based on a time-frequency VAR specification with exogenous control variables. Third, directed and spillover-weighted networks are established for each single time horizon. In this manner, the paper contributes to the existing literature by assessing the effectiveness of the European Banking Union at different time horizons. Moreover, this research not only considers sovereign-bank contagion within a country but analyzes risk transmissions across sovereigns, banks, and borders. The findings of this study demonstrate that the network of sovereign and bank default risk considerably varies across time horizons. While the short and medium-run connectivity reduces after the implementation of the Single Supervision Mechanism in 2014, the null hypothesis of network similarity cannot be rejected in the long run. Nevertheless, the strength of the dependencies reduces across all time horizons and keeps low during the COVID-19 pandemic. This reveals that the SSM is more effective in the short and medium run and emphasizes the informational gain of wavelet analysis. The remaining chapter is structured as follows: Section 2.2 introduces the data and methodological background, while Section 2.3 discusses the results. Finally, Section 2.4 reaches a conclusion.

2.2 Data and methodology

This section describes the empirical approach to establish time-frequency networks of sovereign and bank default risk. A network is generally defined by its nodes and edges. In this paper, the nodes are related to sovereigns and banks, while the directional edges are derived based on Granger causality. Moreover, the specific strength of the dependence between the nodes is estimated by the spillover index of Diebold and Yılmaz (2014). Given N individual sovereigns and banks, this corresponds to estimating $N^2 - N$ dependencies for each time horizon.

2.2.1 Data set

The analysis is based on daily 5-year Credit Default Swap premia for a time period from January 1, 2009, to September 1, 2021, resulting in 3,304 observations. A Credit Default Swap works like an insurance contract, where the policyholder pays a premium to the insurer to receive compensation for losses arising from default (Bratis et al., 2018). Hence, CDS are often perceived as a proxy for default risk, where higher spreads indicate growing market expectations of a default on the underlying debt (Kalbaska and Gątkowski, 2012). In contrast to alternative risk measures, CDS reflect timelier market perceptions unlike company and firm rating announcements and do not have the difficulty of dealing with inflation expectations such as bond yields (Sáiz et al., 2019). In the analysis, daily CDS premia are chosen to provide enough observations for obtaining reliable wavelet and VAR estimates. CDS contracts with a length of 5 years are utilized, as these are the most liquid and actively traded contracts (Bruyckere et al., 2013). All CDS are senior unsecured claims with a modified restructuring clause collected from Refinitiv Eikon. Non-trading weekends are excluded. The sample follows a two-stage selection process. First, the largest 10 economies in the eurozone are selected based on the average GDP over the sample period to capture the core financial stability in the euro area. Second, the banks in each respective country are selected in line with the definition of local and global systemically important institutions published by the European Banking Authority (EBA). This criterion relates to the paper of Borri and di Giorgio (2021), who demonstrate that larger publicly traded European banks are contributing to systematic risk significantly more. In contrast, smaller banks usually do not have traded CDS or the spreads are illiquid (Georgoutsos and Moratis, 2017).[1] Overall, the selected banks represent about 69% of the total

[1] Greece is omitted from the sample, as the country is not among the 10 largest eurozone counties, the sovereign CDS are not priced during the period of consideration, and the bank CDS are illiquid.

bank assets in the euro area and the chosen countries contribute to about 95% of the total GDP in the eurozone (in 2019, prior to COVID-19).[2] Hence, the sample can be assumed to represent the euro area and the banking sector adequately. The United Kingdom and the United States are considered as control countries. Accordingly, the banks are selected in line with the definition of systemically important financial institutions of the Federal Reserve Bank and the Financial Stability Board conditioned on the availability of CDS premia. Table 2.1 lists the selected banks. To capture a country's overall banking sector, country-specific CDS indices are computed as an arithmetic mean of banks in the specific country. The individual weights are based on the total bank assets. Hence, the largest banks of the respective country are weighted more.

Country	Bank	Weight	Country	Bank	Weight
DE	Deutsche Bank	0.56	ES	BBVA	0.29
DE	Commerzbank	0.22	ES	Banco Sabadell	0.09
DE	LBBW	0.12	ES	Bankinter	0.03
DE	BayernLB	0.10	NL	ING-DiBa	0.61
FR	BNP Paribas	0.42	NL	Rabobank	0.39
FR	Crédit Agricole	0.35	BE	KBC	1.00
FR	Société Générale	0.23	AT	Erste Group Bank	0.88
IT	UniCredit	0.45	AT	BAWAG P.S.K.	0.12
IT	Intesa Sanpaolo	0.44	IE	Bank of Ireland	1.00
IT	Monte dei Paschi	0.07	FI	Nordea	1.00
IT	Mediobanca	0.04	PT	Banco Comercial Português	0.49
ES	Banco Santander	0.60	PT	Caixa Geral de Depósitos	0.51
Control countries					
US	J.P. Morgan	0.25	UK	HSBC	0.39
US	Bank of America	0.25	UK	Barclays	0.23
US	Citigroup	0.20	UK	Lloyds Banking Group	0.14
US	Wells Fargo	0.17	UK	Natwest	0.13
US	Morgan Stanley	0.10	UK	Standard Chartered Bank	0.10
US	Capital One	0.04			

For each bank and related sovereign, 5-year CDS premia are obtained from Refinitiv Eikon. The weights are based on the average asset values of the EU-wide transparency exercise conducted by the EBA in 2016 and 2021. These weights are used to build country-specific bank CDS measures. The country codes are as follows: DE: Germany, FR: France, IT: Italy, ES: Spain, NL: Netherlands, BE: Belgium, AT: Austria, IE: Ireland, FI: Finland, PT: Portugal, US: United States, UK: United Kingdom.

Table 2.1: Description of banks in the sample

[2] European Central Bank (2019) - Consolidated Banking Data and Eurostat (2019): 'Which member states contributed the most to the GDP in 2019'.

2.2.2 Maximal overlap discrete wavelet transformation

In the first step, Maximal Overlap Discrete Wavelet Transformation (MODWT) is applied to decompose bank and sovereign CDS premia into multi-horizon components. In general, a wavelet is a function that splits a signal into different components that reflect the evolution through time and at particular frequencies. Standard econometric methods, such as co-integration, vector autoregression, or switching regime models, in contrast, only operate within the time domain (Singh et al., 2018; Masset, 2014). The technique ordinates from the field of electrical engineering, where wavelet transformation is used to analyze local signals. Due to its main advantages, the method rapidly spread out and has been applied in several other areas, such as epidemiology, neuroscience, climatology, and oceanography. The application to the field of economics and finance is relatively recent, yet the range of implementation is potentially wide (Bales and Burghof, 2022). The econophysics literature shows that wavelet tools yield robust estimates of non-stationary time series and are able to account for non-linearity in financial data (Hkiri et al., 2016). In line with the existence of boom and recession periods, the relation between sovereign and bank default risk is likely to vary within a business cycle and at different frequencies. For this reason, the study combines MODWT with conventional econometric methods to analyze data on a time and frequency domain. Considering discrete transformation tools, the Maximal Overlap DWT framework has some advantages over the classical Discrete Wavelet Transform (DWT), as it overcomes adverse effects related to the choice of a starting point. Furthermore, the MODWT does not require a dyadic length of the data and therefore avoids phase shifts which would change the location of events over time (Feng et al., 2018; Yang, 2019). Following Ramsey (2002), any function of time can be represented as a sequence of projections by father Φ and mother Ψ wavelets. Father wavelets capture the long-run smooth components and integrate to one, while mother wavelets define the deviations from the smooth components and integrate to zero (Gupta et al., 2018). Based on father and mother wavelets, scaling and translation coefficients are derived. Let $\Delta Y(t) = ln(CDS_t/CDS_{t-1})$ define a sequence of daily CDS premia changes, the wavelet representation is given by a linear combination of wavelet functions

$$\Delta Y(t) = \sum_k S_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \cdots + \sum_k d_{j,k}\psi_{j,k}(t) + \cdots + \sum_k d_{1,k}\psi_{1,k}(t), \quad (2.1)$$

which can be written in simplified notation as

$$\Delta Y(t) = S_J(t) + D_J(t) + D_{J-1}(t) + \cdots + D_j(t) + \cdots + D_1(t) \quad (2.2)$$

with the orthogonal components given by $S_J(t) = \sum_k S_{J,k}\phi_{J,k}(t)$ and $D_J(t) = \sum_k d_{j,k}\psi_{j,k}(t)$ for $j = 1, 2, \ldots, J$. The highest-level approximation $S_J(t)$ is a smooth signal, while the detailed signals $D_1(t)$, $D_2(t)$, $\ldots$, $D_J(t)$ are related to oscillations of lengths 2, 4, $\ldots$, and 2^J (Gourène et al., 2019). In this study, $\Delta Y(t)$ is decomposed into six components, $D_1(t)$ to $D_6(t)$, to cover a time horizon of up to 128 trading days (approximately half a year). This selection of J is based on the wavelet variance decomposition, indicating that components D_5 and D_6 capture only 1–5% of the variation in CDS premia (Table 2.3). Thus, a higher decomposition level of $J > 6$ does not provide more information. The range and interpretation of each component are summarized in Table 2.2. Following Belhassine and Karamti (2021) and Gupta et al. (2018), the short run is defined by D_1 and D_2, the medium horizon by D_3 and D_4, and the long run by D_5 and D_6.

Scale	Range	Interpretation	Scale	Range	Interpretation
D_1	2–4	Intra-weekly	D_4	16–32	Monthly
D_2	4–8	Weekly	D_5	32–64	Monthly to quarterly
D_3	8–16	Fortnightly	D_6	64–128	Quarterly to biannual

The short horizon is defined by D_1 and D_2, the medium horizon by D_3 and D_4, and the long horizon by D_5 and D_6. The trend level is discarded due to a lack of economic interpretation (128 trading days to infinity).

Table 2.2: Wavelet scale interpretation

The wavelet decomposition is implemented by the pyramidal algorithm visualized in Figure 2.2. 'HPF' and 'LPF' denote High-Pass Filter and Low-Pass Filter related to the applied wavelet and scaling filters. In the MODWT framework, both filters are numerically derived from Daubechies (1988) least asymmetric filter of length 8, named LA(8). The LA(8) belongs to the family of orthogonal wavelets and delivers outcomes that are less correlated across scales in contrast to the Haar wavelet (Gupta et al., 2018). Afterward, the multi-scale variance $\sigma^2_{Y,j}$ can be estimated by the average of squared wavelet coefficients across each scale (Percival and Walden, 2000). Accordingly, the covariance $\sigma_{XY,j}$ between the wavelet coefficients of two series $X(t)$ and $Y(t)$ is computed. Finally, the MODWT estimator of the wavelet correlation at scale j is defined as

$$p_{XY,j} = \frac{cov\{D_{X,j}, D_{Y,j}\}}{\sqrt{var\{D_{X,j}\}var\{D_{Y,j}\}}} = \frac{\sigma_{XY,j}}{\sigma_{X,j}\sigma_{Y,j}}, \tag{2.3}$$

where wavelet coefficients affected by the boundary condition are removed to obtain unbiased estimates (Conlon et al., 2008; Reboredo and Rivera-Castro, 2014). The MODWT is

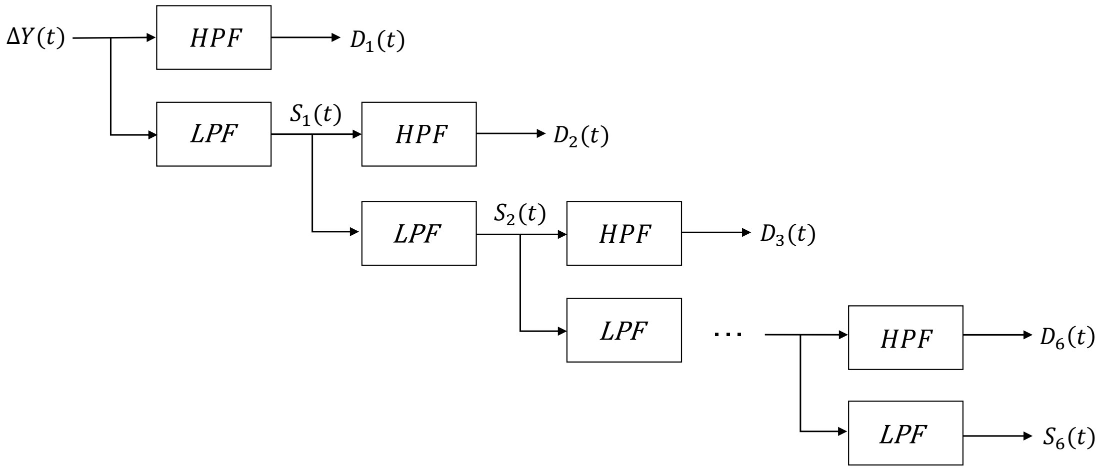

Figure 2.2: Illustration of multi-resolution analysis

conducted using the *waveslim* package in R. Accordingly, the wavelet variance and correlation are estimated with this package. Finally, country-specific banking sector indices are computed as an arithmetic mean of the wavelet components using the weights indicated in Table 2.1.

2.2.3 Time-frequency vector autoregressive model

After MODWT, a time-frequency Vector AutoRegressive Model (VAR) is estimated to derive directional edges between all pairs of sovereigns and banks.[3] Once causal relationships are derived, the edges are weighted by the spillover index of Diebold and Yılmaz (2014) in a second step. This approach provides several advantages, as it does not consider insignificant linkages in contrast to the spillover network approach of Diebold and Yılmaz (2014) and improves the unweighted networks of Gomez-Puig et al. (2019), Brunetti et al. (2021), and Yang (2019). A major problem in quantifying the causal connectivity is the co-movement of sovereign and bank risk due to potentially unobservable factors. Financial market shocks may trigger an increase in sovereign CDS, which can affect banks' profitability simultaneously through a different channel (Covi and Eydam, 2020). To overcome this issue, a VAR with exogenous control variables is specified as

$$Y_t = C + \sum_{i}^{k} \Phi_i Y_{t-i} + \sum_{m} \beta_m EXO_{m,t} + \epsilon_t; \qquad \epsilon_t \sim id(0, \textstyle\sum_{\epsilon}), \tag{2.4}$$

[3]The hypothesis of non-linearity in the relationship between sovereign and bank CDS is rejected for all countries and wavelet scales.

where Y_t is a $[N \times 1]$ vector of endogenous variables containing sovereign and banking sector default risk for a given horizon j

$$Y_t = \left[D^{sov}_{j,DE}(t), \ldots, D^{sov}_{j,PT}(t), D^{bank}_{j,DE}(t), \ldots, D^{bank}_{j,PT}(t)\right]'. \tag{2.5}$$

Furthermore, Φ_i is a $[N \times N]$ matrix containing the autoregressive coefficients and ϵ_t is an independent distributed white noise process. Moreover, C represents a $[N \times 1]$ vector of constants and $EXO_{m,t}$ relates to a series of macroeconomic and financial variables decomposed at scale j. To control for the overall business climate in the European Union, the STOXX Europe 600 stock market index is included. The index represents 600 companies with large, mid, and small capitalization in 17 European countries. Accordingly, the MSCI world is employed as a global factor. To take the market-wide financial uncertainty or market sentiment into account, the VSTOXX and VIX volatility indices are considered. The indices measure the implied volatility of options written on the STOXX Europe 50 and the S&P500. Lending and interbank market conditions are captured by the euro overnight interest average rate (Eonia) and the Euribor-Eonia spread.[4] For the U.S. market, the TED spread is used accordingly. Moreover, long-term and short-term macroeconomic risk indicators and default risk indices are considered: The iTraxx Europe relates to the most liquid 5-year CDS in Europe based on 125 companies. The iTraxx crossover and iTraxx senior financial measure cross-country risk spillover and financial sector-specific default risk respectively. Finally, sovereign and bank default risks in the U.S. and U.K. are kept constant by including sovereign and bank CDS indices. Comprehensive descriptions of the control variables are provided in Table 2.6 (Appendix). The model is estimated with two lags for the endogenous variables and contemporaneous exogenous variables based on the information criterion of Akaike (1974). After estimation, Granger causality between all pairs of sovereigns and banks is assessed. The related Wald test statistic is given by

$$WT = \left[e \times vec\left(\hat{\Phi}\right)\right]' \left[e\left(\hat{V} \otimes (Y'Y)^{-1}\right)e'\right]^{-1} \left[e \times vec\left(\hat{\Phi}\right)\right], \tag{2.6}$$

where Y is a matrix of independent variables referring to Equation (2.4), $vec(\hat{\Phi})$ denotes the row vectorized coefficients of $\Phi = [\Phi_1, \ldots, \Phi_k]$, and $\hat{V} = T^{-1}\sum_{t=1}^{T} \hat{\epsilon}_t \hat{\epsilon}_t'$. Finally, e is the selection matrix, where one of the coefficients in each row is set equal to zero under the null hypothesis of non-causality (Dungey et al., 2019).

[4]Note: Starting on October 2, 2019, the Eonia rate is replaced by €STR + 8.5 basis points to take the transition phase towards the new rate €STR into account.

2.2.4 Weighted network specification

The Granger causality results are used to build an asymmetric adjacency matrix with binary entries $A = [a_{ij}]$, where $a_{ij} = 1$ in the case of Granger causality at a level of 5% significance and $a_{ij} = 0$ otherwise. Significant causality from sovereign or bank j to sovereign or bank i indicates that the default risk of entity j predicts the default risk of entity i at a given time horizon (Dungey et al., 2019). As a final step, weights $W = [w_{ij}]$ are assigned to the edges to quantify the strength of the dependence. Following Diebold and Yılmaz (2012) and Diebold and Yılmaz (2014), the weights are obtained by the generalized spillover index. The method is based on the generalized variance decomposition introduced by Koop et al. (1996) and has the advantage of not being dependent on the ordering of variables in contrast to the application of Cholesky factorization to achieve orthogonality. Following Equation (2.4), the contribution of variable j to the H-step-ahead generalized forecast error variance of variable i is computed by

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \sum e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \sum A_h' e_i)}; \qquad H = 1, 2, \ldots, \tag{2.7}$$

where $\sum$ represents the covariance matrix for the error vector ϵ, σ_{jj} is the standard deviation of the error term for the jth equation, and e_i is the selection vector with one as the ith element and zeros otherwise. Finally, A_h is a h-step moving average coefficient matrix related to the moving average representation of the VAR system. In this paper, a forecast horizon of one week is chosen. When applying the generalized spillover framework, the shocks are not orthogonalized and the contributions to the variance of the forecast error do not sum up to one (Diebold and Yılmaz, 2014). Therefore, all entries of the variance decomposition matrix are normalized by the row sum in line with

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)}, \tag{2.8}$$

where $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = N$ by construction (Diebold and Yılmaz, 2014). The directional spillovers transmitted from sovereign or bank j to sovereign or bank i are calculated as

$$\begin{aligned} S_{j \to i}^{g}(H) &= \frac{\sum_{j=1, j \neq i}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \times 100 \\ &= \frac{\sum_{j=1, j \neq i}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \times 100. \end{aligned} \tag{2.9}$$

The estimation of the spillovers w_{ij} is conducted with the package *Spillover* in R. Finally, the overall structure of the network is defined by the weighted adjacency matrix

$$\tilde{A} = A \odot W = \begin{bmatrix} a_{11} & \cdots & a_{1j} \\ \vdots & \ddots & \vdots \\ a_{i1} & \cdots & a_{ij} \end{bmatrix} \odot \begin{bmatrix} w_{11} & \cdots & w_{1j} \\ \vdots & \ddots & \vdots \\ w_{i1} & \cdots & w_{ij} \end{bmatrix}, \tag{2.10}$$

where $\odot$ denotes the Hadamard product. Consequently, $\tilde{A}$ captures the spillover-weighted connections between all pairs of sovereigns and banks conditional on significant and directional linkages between them.

2.3 Results and discussion

The following section evaluates the estimated time-frequency networks by addressing several network statistics. In a first step, the importance of the extracted multi-scale components is assessed based on a scale decomposition of sovereign and bank CDS volatility.

2.3.1 Sovereign and bank wavelet variance

Table 2.3 reports the contribution of component D_j to the overall variance by country. Considering sovereign default risk, about 39% to 66% of the overall variance can be attributed to short-run fluctuations associated with a time horizon of 2–4 trading days. Interestingly, the sovereign variance in financially distressed countries, such as Italy, Spain, Portugal, and Ireland, is less impacted by short-run factors but is more varying in the medium run. Considering a time horizon of 16–128 days (D_4, D_5, and D_6), the scale-specific variance contributions are less than 10%. This indicates high volatility in the short run, while the fundamental level of default risk priced by the market is almost stable. The conclusions for bank default risk are accordingly, but the short-run contribution is more evenly distributed across countries. Overall, this may point to higher sovereign-bank dependence in the long run. The findings are in line with the descriptive statistics reported in Tables 2.8 and 2.9 (Appendix), where the short-run components are characterized by high standard deviation and great excess kurtosis, indicating heavy outliers.

2.3.2 Time-frequency contagion networks

To address the impact of the European Banking Union and the COVID-19 epidemic, the sample is divided into 3 sub-samples. The first sub-sample considers the developments

	Sovereign CDS variance (%)						Bank CDS variance (%)					
	D_1	D_2	D_3	D_4	D_5	D_6	D_1	D_2	D_3	D_4	D_5	D_6
DE	59	24	10	4	2	1	49	25	14	6	3	2
FR	53	24	12	6	3	1	44	26	16	7	4	2
IT	40	27	18	8	4	2	41	27	16	8	5	2
ES	40	27	18	8	4	2	48	26	14	6	3	2
NL	66	21	6	2	1	0	50	24	13	6	4	2
BE	57	24	11	5	2	1	51	25	12	6	3	2
AT	48	26	12	8	4	2	52	25	12	6	3	2
IE	42	27	20	7	3	1	56	24	10	5	2	2
FI	62	21	9	4	2	1	50	25	12	6	4	2
PT	39	26	19	8	5	2	47	24	15	7	4	3

This table depicts the percentage contribution of component D_j to the overall sovereign and bank CDS variance by country. The contribution of the jth component is calculated by $[\sigma^2_{Y,j} / \sum_{j=1}^{6} \sigma^2_{Y,j}] \times 100$. The trend level S_6 is discarded due to a contribution of less than 0.1%.

Table 2.3: Distribution of sovereign and bank CDS variance by country and scale

of the European debt crisis following the financial crisis between 2009 and 2014. The second period relates to the implementation of the Banking Union. Since the SSM was the first pillar to become operational in November 2014, the starting point of the second sub-sample is defined accordingly (Houben and Vandenbruwaene, 2017). In January 2016, also the Single Resolution Mechanism (SRM) entered fully into force. The last sub-sample captures the beginning and the development of the COVID-19 pandemic in 2020–2021. The specific dates are depicted in Table 2.4.

Sample	Characteristic	Start	End	Observations
S1	European debt crisis	Jan. 1, 2009	Oct. 31, 2014	1,522
S2	EBU introduction	Nov. 1, 2014	Dec. 31, 2019	1,349
S3	COVID-19 pandemic	Jan. 1, 2020	Sep. 1, 2021	432

Table 2.4: Description of the sub-samples

Figures 2.3, 2.4, and 2.6 visualize the networks by sub-sample and scale. Sovereigns are indicated by gray nodes, while banks are colored in blue. The specific location of the nodes is determined by the algorithm of Fruchterman and Reingold (1991) applied at scale D_6. The Fruchterman-Reingold is one of the most used force-directed layout algorithms, which applies an iterative process to choose the placement of the nodes for minimizing the energy of a system. As a result, nodes that share more connections are located closer to each other. Outgoing edges are visualized in the same color scheme as the nodes, where the arrowhead indicates the direction of causality. Finally, the thickness of the edges represents the strength of the dependence between nodes. The network graphs and related statistics are based on the package *igraph* in R.

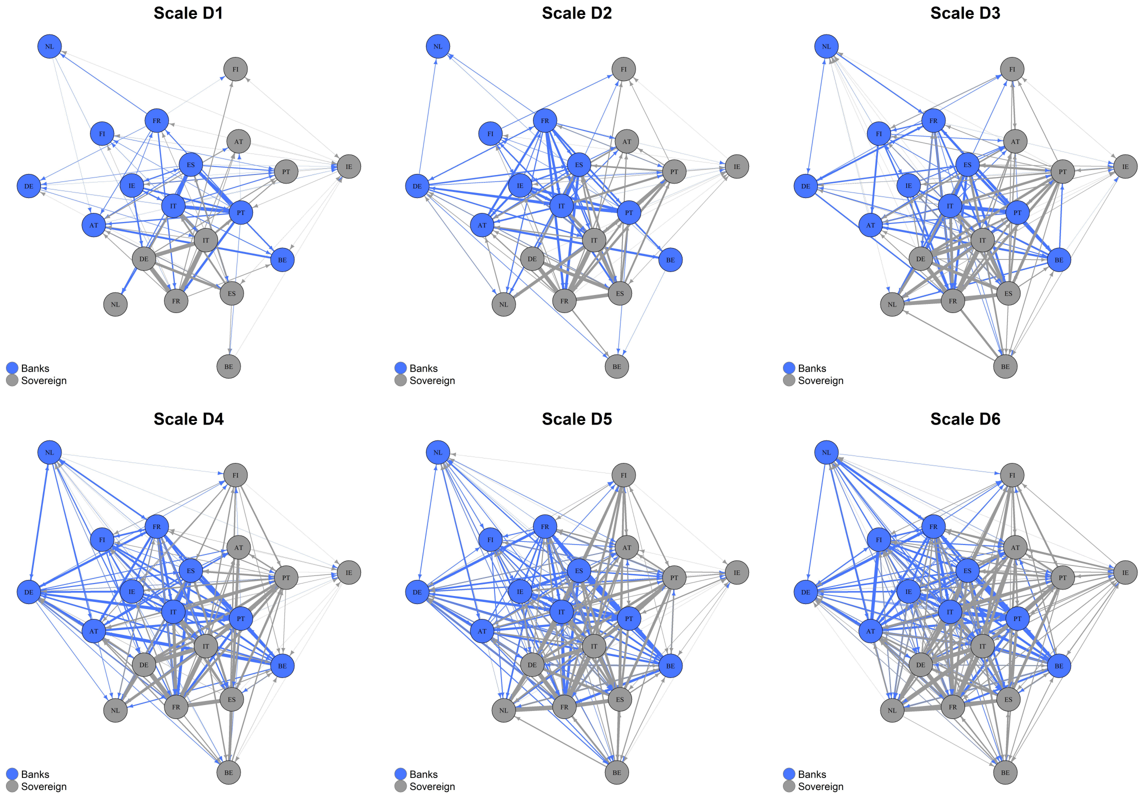

Figure 2.3: Sovereign-bank default risk network: January 2009 to October 2014

Considering sub-sample 1 in Figure 2.3, the center of the network is characterized by banks located in Portugal, Italy, Ireland, and Spain. Together with Greece, these countries came to be known as the *PIIGS*[5] in the framework of the European debt crisis. The economic downturn in Greece triggered a wave of financial contagion, affecting the stability of the PIIGS and threatening the survival of the single currency (Kalbaska and Gątkowski, 2012). In accordance, the thickness of the edges indicates heavy dependence between the PIIGS countries in the very short run (2–4 days). Apart from banks, the network shows strong short-run default risk dependencies between the sovereigns of the core eurozone members Germany, France, Italy, and Spain. In the medium and long horizon, the default risk dependencies are more pronounced. The network density is con-

[5]PIIGS: **P**ortugal, **I**taly, **I**reland, **G**reece, and **S**pain.

tinuously increasing with j, where contagion between banks and sovereigns (blue versus gray edges) seems to be balanced. The network is highly concentrated in the 64–128 days horizon and the countries, which are not affected in the short run, are now part of the network due to heavy risk spillovers. In the course of the crisis, the European Union and the International Monetary Fund agreed on bailout packages for Ireland, Portugal, and Greece. These bailouts did not eliminate risk but caused heavy indebtedness of the PIIGS and transferred the risk to governments of other European countries (Kalbaska and Gątkowski, 2012; Böhm and Eichler, 2020; Breckenfelder and Schwaab, 2018).

Taking a view on Figure 2.4, the networks show strong evidence that the new regulatory framework has been effective in reducing credit risk transmissions across all scales. The effect is more pronounced in the short run. While the center of the network is still characterized by banks located in Italy, Spain, and Portugal, the number, and more importantly, the strength of the linkages is significantly lower. Furthermore, sovereigns and banks cluster together. By the definition of the node placement in the Fruchterman-Reingold algorithm, this indicates lower contagion between sovereigns and banks.

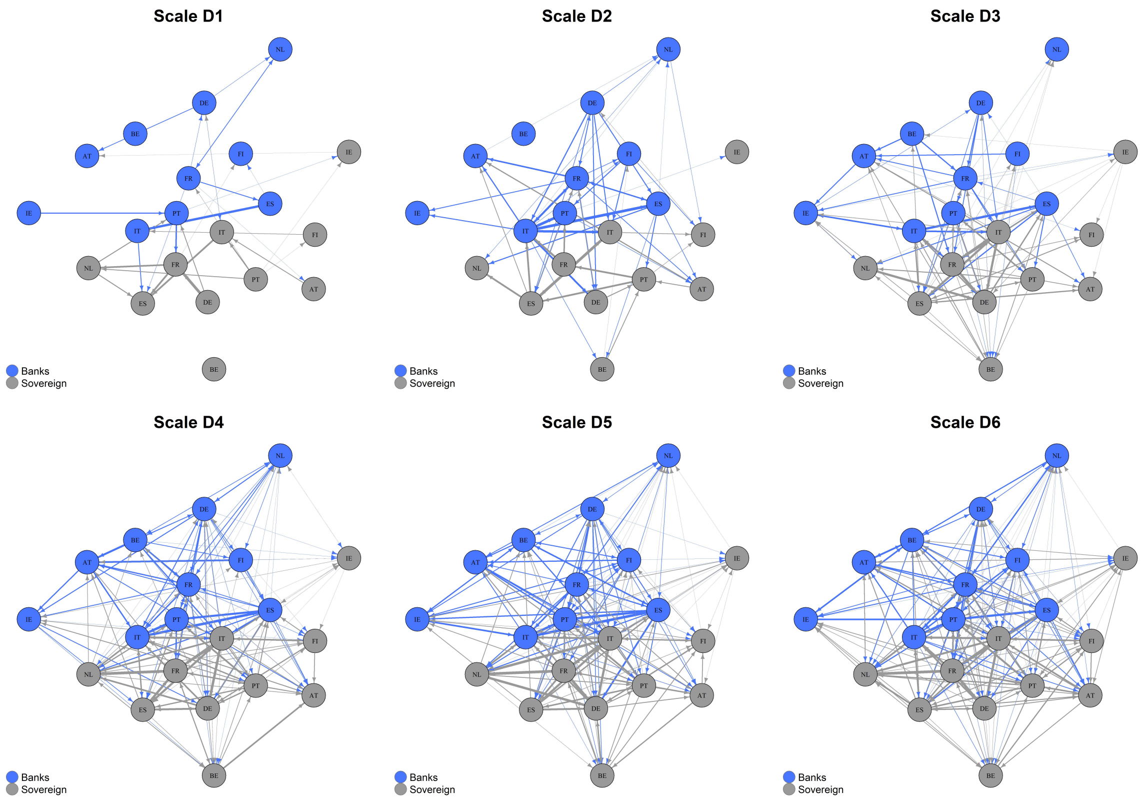

Figure 2.4: Sovereign-bank default risk network: November 2014 to December 2019

Economically, a standardized regulatory framework restores confidence in the financial system, strengthens the integration of the banking sector, and reduces idiosyncratic risk caused by coordination failure at the national level (Covi and Eydam, 2020). The application of common rules, furthermore, leads to more homogeneous funding conditions and makes banks less dependent on domestic sovereign risk. Since the SSM allows the direct intervention of the European Stability Mechanism to offer temporary financial assistance, the costs of government bailouts are potentially lowered, which weakens contagion between sovereigns and banks (Sáiz et al., 2019). Prior research shows evidence that the SSM positively impacts the profitability of directly supervised banks (Avgeri et al., 2021).[6] However, the sovereign-bank network is still moderately connected in the medium and long run. Breckenfelder and Schwaab (2018) argue that the Security Supervision Mechanism not only promoted financial stability but also introduced a framework for potential risk transmissions. Moreover, Uhlig (2014) points to the risk-shifting hypothesis and argues that the European Monetary Union implicitly shifts sovereign default risk onto the balance sheet of the ECB and the rest of the Eurosystem by delivering underpriced loans from banks to their sovereigns. This eurozone effect may explain the persistence of connectivity in the medium and long horizon. A second issue relates to the home bias. Figure 2.5 illustrates the annual growth rate of sovereign debt held by domestic banks.[7]

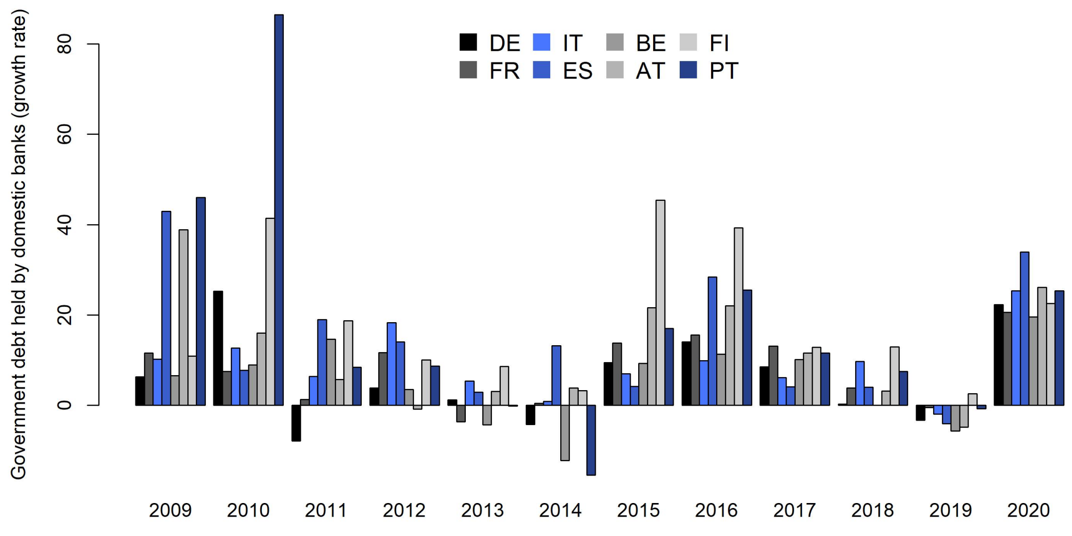

Figure 2.5: Annual growth rate of government debt held by domestic banks

[6]The stepwise implementation of Basel III comprising stricter capital requirements for banks may positively contribute to the observed results. The regulation should initially be implemented by 2015 but has been postponed several times. Because of COVID-19, the implementation is now due in 2025.

[7]European Central Bank (2022). Data for the Netherlands and Ireland are not available.

While the growth is low over the period 2013–2014, domestic banks started to increase their exposure to government bonds in the following years. The figure also highlights large-scale purchases of sovereign debt securities as a response to the economic downturn triggered by the COVID-19 pandemic. In March, April, and May 2020, eurozone banks increased their domestic exposure by 61 bn, 82 bn, and 52 bn euro, which constitutes the largest growth in three consecutive months ever recorded (+10%). Putting the change in relation to the GDP of the respective year, the increase in exposure due to the COVID-19 pandemic even exceeds the magnitude of the European debt crisis (Figure 2.9, Appendix). In addition, banks expanded their claims on other euro area sovereigns by 13%.[8]

In accordance with these findings, Figure 2.6 reveals that the connectivity of the network in sub-sample 3 is significantly greater. While sovereigns and banks tend to cluster in sub-sample 2, this is not the case during the pandemic, indicating higher contagion between both. Increasing uncertainty and threatening economic risks of the pandemic outbreak led households to reduce consumption, while firm investments and credit demand decreased. As uncertainty bears risk, banks tend to further tighten their lending activity by rigorous monitoring of their borrowers, which lowers bank profits (Elnahass et al., 2021; Swamy, 2013). Not least because of governmental lockdown policies and threatening payment defaults of creditors, bank default risk increased sharply. In addition, sovereign CDS premia rose as European governments were faced with lower tax revenues and increasing public debt to stimulate the economy. The effects are further amplified by cross-country risk transmissions. Guo et al. (2021) even indicate that the COVID-19 epidemic increased the number of contagion channels in the international financial system. Nevertheless, the nodes in Figure 2.6 are less closely located to each other and the risk spillovers, measured by the edges' thickness, remain at low levels. Overall, the network is less heavily connected compared to 2009–2014, which provides evidence of a successful implementation of the Banking Union, even in times of financial distress.

2.3.3 Assessing network statistics

To statistically evaluate and compare the different network structures, several measures are considered. First, the *network density* is calculated as the ratio of edges to the number of possible edges. Second, *network reciprocity* is defined as the overall proportion of reciprocated ties, indicating default risk loops between two nodes. Third, *edge strength* reports the average strength of the connection and relates to the weighted adjacency matrix $\tilde{A}$.

[8] European Central Bank (2022) - Government Finance Statistics.

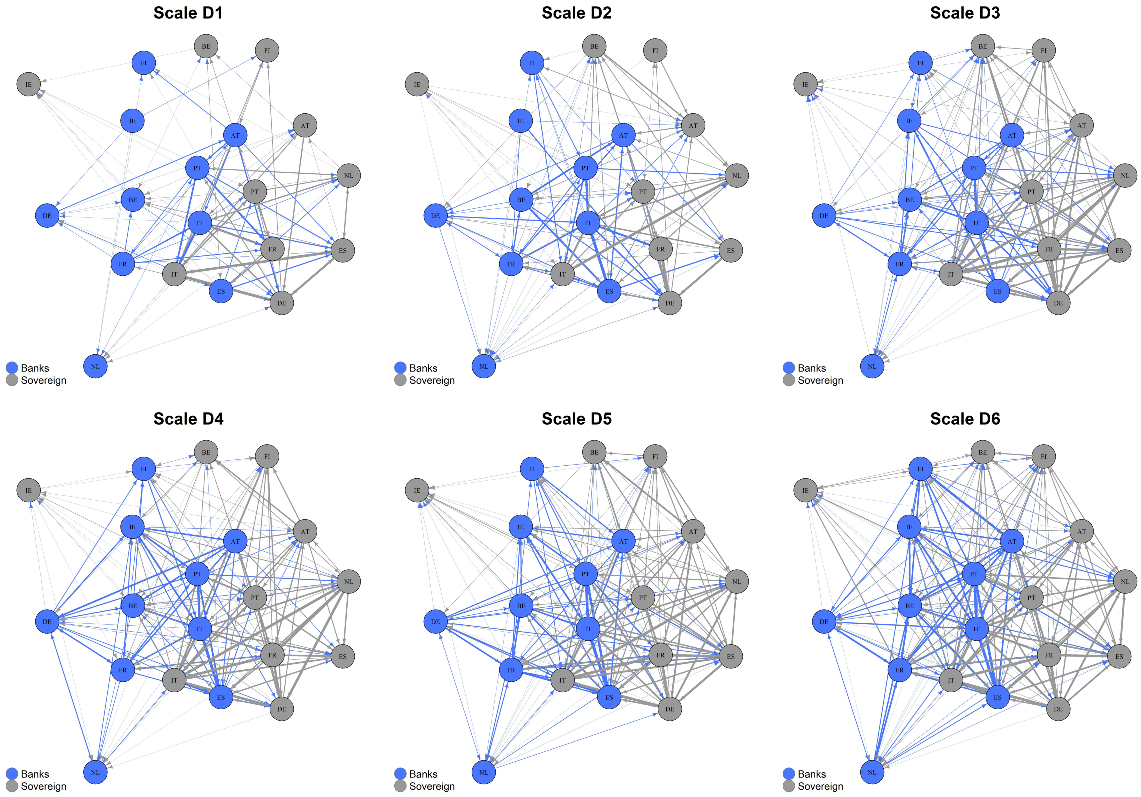

Figure 2.6: Sovereign-bank default risk network: January 2020 to September 2021

Fourth, *domestic nexus* indicates the proportion of two-way relationships between domestic sovereign and bank CDS. In contrast to reciprocity, which also considers cross-country and sovereign-sovereign or bank-bank loops, this measure specifically addresses the home bias. Finally, *Jaccard similarity* coefficients are estimated to compare the network structures. The Jaccard index is a commonly used statistical measure to compare the similarity of binary matrices.[9] Given two samples S_i and S_j, Jaccard similarity is defined as the size of the edge intersection of both samples

$$J(S_i, S_j) = \frac{|S_i \cap S_j|}{|S_i \cup S_j|} = \frac{|S_i \cap S_j|}{|S_i| + |S_j| - |S_i \cap S_j|}. \tag{2.11}$$

The coefficient is normally distributed and ranges between $J(S_i, S_j) \in [0,1]$, where values close to 1 indicate high similarity. If $J(S_i, S_j) < 0.5$, the null hypothesis of equal connectedness in two samples is formally rejected (Dungey et al., 2019; Nobi et al., 2014).

[9]As Jaccard similarity is only defined for binary data (unweighted adjacency matrix A), it delivers conclusions about the similarity of the connectivity, but not about the strength of the dependence.

		D_1	D_2	D_3	D_4	D_5	D_6
Network density	*S1*	0.22	0.30	0.39	0.47	0.61	0.70
	S2	0.08	0.16	0.26	0.45	0.49	0.59
	S3	0.27	0.34	0.47	0.48	0.55	0.65
Network reciprocity	*S1*	0.31	0.35	0.40	0.51	0.64	0.84
	S2	0.12	0.23	0.37	0.51	0.49	0.57
	S3	0.37	0.43	0.51	0.48	0.54	0.63
Edge strength	*S1*	0.26	0.35	0.45	0.53	0.70	0.93
	S2	0.08	0.15	0.25	0.43	0.46	0.50
	S3	0.21	0.26	0.35	0.37	0.43	0.49
Domestic nexus	*S1*	0.40	0.40	0.60	0.70	0.70	0.70
	S2	0.00	0.10	0.20	0.30	0.30	0.30
	S3	0.10	0.20	0.20	0.40	0.40	0.60
Jaccard similarity	*S1 & S2*	0.24	0.32	0.39	0.48	0.54	0.58
	S2 & S3	0.31	0.39	0.44	0.49	0.56	0.56
	S1 & S3	0.42	0.45	0.48	0.48	0.57	0.53

The *'Network density'* is calculated as the ratio of edges to the number of possible edges. The *'Network reciprocity'* is defined as the overall proportion of reciprocated ties. *'Edge strength'* reports the average strength of the connection. *'Domestic nexus'* indicates the proportion of two-way relationships between domestic sovereign and bank CDS. *'Jaccard similarity'* relates to the comparison of two network densities and does not consider the strength of the dependence. For *'Jaccard similarity'* < 0.5, the null hypothesis of equal connectedness between two samples is rejected.

Table 2.5: Sovereign-bank network statistics

Table 2.5 confirms that the connectivity increases with the time horizon. This effect is observed for all sub-periods. Comparing $S1$ and $S2$, the network density is considerably lower after the introduction of the new regulatory framework. Besides a lower density, the network reciprocity shows a lower number of two-way contagion relationships. The Jaccard similarity coefficients indicate that these effects are mainly pronounced in the short and medium run, as the null hypothesis of equal connectedness is rejected for scales D_1 to D_4. In the long run, the null hypothesis of similarity cannot be rejected. Nevertheless, the lower value of edge strength shows less tight risk dependencies even in the long run. This consolidates the prior conclusion that the SSM affects both, the connectivity (mostly in the short horizon) and the strength of the dependencies across all scales. Comparing sub-samples $S2 - S3$ and $S1 - S3$, the network structures are likewise concluded to differ at scales D_1 to D_4. This reveals that the COVID-19 pandemic has increased the network density and network reciprocity in the short and medium run but to a lower extent than during the European debt crisis. Relating to the home bias, a nexus of domestic sovereign and bank default risk exists in 3 out of 10 countries in sample $S2$, while the pandemic brought back this issue (6/10). Due to its importance for financial stability, the next subsection specifically addresses this nexus by considering the countries separately.

2.3.4 The domestic sovereign-bank nexus

The home bias in banks' sovereign bond holdings is extensively discussed in the literature. By investing in domestic government bonds, banks can earn the entire risk premium, while the risk itself is mainly borne by their creditors (Andreeva and Vlassopoulos, 2019). Figure 2.7 depicts the wavelet correlation of domestic sovereign and bank risk by sub-sample and country. In almost all of the countries, the wavelet correlation is significantly lower in the second sub-sample (blue line). The effect applies to all scales, while the correlation is, on average, higher in the long run. These results are in accordance with Covi and Eydam (2020) and Sáiz et al. (2019), who indicate a weakening of the doom loop after 2015. Considering the pandemic period (dashed line), the wavelet correlation raises again and even reaches higher levels than in the first sub-sample in some countries. These findings can be attributed to the observed large-scale purchases of sovereign debt securities during the pandemic. In contrast, the correlation in Italy seems to be constant over the 3 sub-samples. The observation can be explained by turmoil in the banking sector. In 2016, a 20 bn euro rescue fund has been approved by the Italian parliament to bailout Banca Monte dei Paschi di Siena[10] followed by the bailouts of Banca Popolare di Vicenza and Veneto Banca[11] in 2017. These bailouts aroused public interest, as their treatment deviated strongly from the bank resolution requirements. Unlike intended by the SRM, the banks were rescued or merged into other banks without the full bail-in of bondholders. As a result, Popolare di Vicenza and Veneto were acquired by Intesa Sanpaolo for a symbolic 1 euro. Donnelly and Asimakopoulos (2019) argue that the European Commission bent and broke the law by turning a blind eye to infractions in Italy. This example sheds critical light on the effectiveness of the implementation of the EBU. Furthermore, Bales (2022*a*) highlights the importance of political turmoil on financial stability. Triggered by the Italian parliament election in March 2018, weeks of uncertain negotiations retrieved the fears of a European debt crisis caused by excessive spending intended by the new government. This ultimately enhanced the correlation between sovereign and bank CDS.

[10] European Parliament (2016) - 'The precautionary recapitalization of Monte dei Paschi di Siena'.

[11] European Parliament (2017) - 'The orderly liquidation of Veneto Banca and Banca Popolare di Vicenza'.

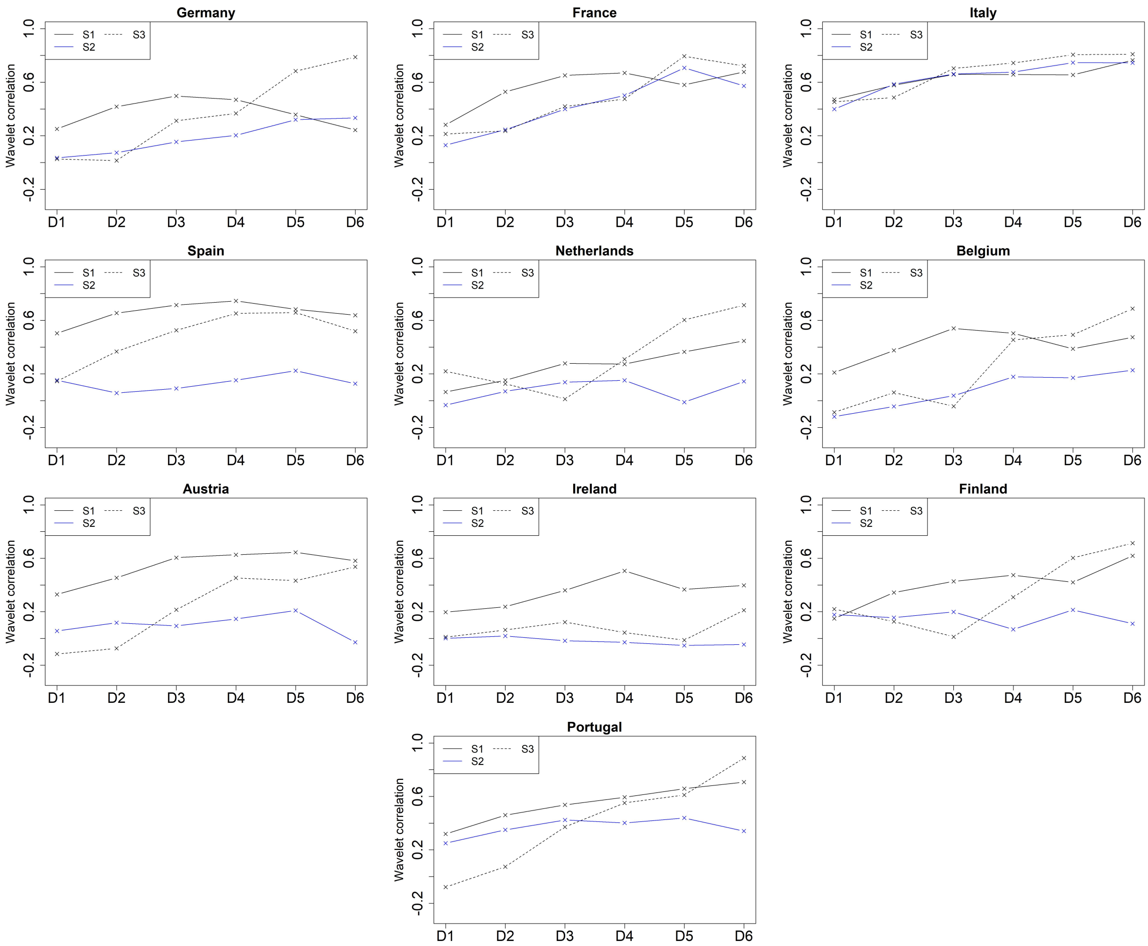

Figure 2.7: Wavelet correlation of sovereign and bank CDS by sub-sample and country

2.3.5 Robustness of the results

To verify the conclusions derived from the network specification, Principal Component Analysis (PCA) is applied. PCA decomposes the total default risk of a sample into orthogonal factors of decreasing explanatory power, where the first principal component captures the largest proportion of commonality (Abdi and Williams, 2010). A detailed description of the method is included in the Appendix. The analysis relates to the CDS of eurozone banks and their associated sovereigns listed in Table 2.1 ($N = 34$). The PCA is separately conducted for each year and scale. Figure 2.8 graphs the common source of default risk underlying the network structure of sovereign and bank CDS associated with the first and second principal components. Considering D_1 and D_2, between 20% and 60% of the overall variation in sovereign and bank default risk can be attributed to the first component, while the second PC describes 5%–16%. This contribution increases with the time horizon, reaching levels between 41% and 78% at scale D_6. While the commonality is the lowest during the period 2014–2019, it is the highest during the European debt crisis and the COVID-19 pandemic. A higher commonality in default risk can be related to a higher level of systematic risk, which drives spillovers between sovereigns and banks. Thus, the PCA supports the network dependence structures and shows moderate commonality in the short run, while highlighting the persistence of connectivity in the long run.

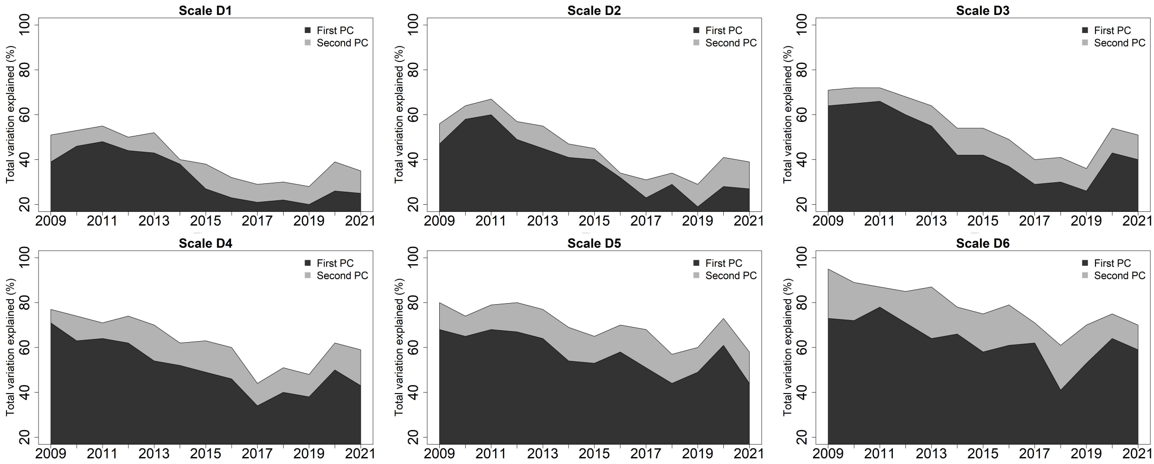

Figure 2.8: Percentage of default risk variation explained by the first and second principal components

As a second robustness check, the VAR model of Equation (2.4) is estimated using lag lengths of $i = \{1, 3\}$. The implementation makes little qualitative difference to the results obtained from the VAR(2) suggested by the AIC. Chan-Lau (2006) accordingly finds little sensitivity in network estimation to a change in the lag length. Similarly, the spillover index is calculated for forecast horizons varying from 6 to 10 days, providing equal measures of the edge strength. Third, the frequency dimension is discarded and the networks are established without preceding wavelet transformation. Referring to Figure 2.13 and Table 2.7 in the Appendix, the network is significantly less connected after the introduction of the SSM. In contrast, the pandemic increased the connectivity again. The estimated density, reciprocity, and edge strength seem to be an average of the prior network statistics across wavelet scales. Assessing Jaccard similarity, the null hypothesis of similarity cannot be rejected when comparing the European debt crisis and the COVID-19 pandemic. For the remaining sub-samples, the coefficients differ only marginally and are close to the threshold of 0.5. This highlights the informational gain of applying wavelet transformation to understand the frequency structure of contagion. Finally, changes in the calculation of country-specific banking sector indices are assessed. Instead of computing the indices after decomposition, the averages are calculated beforehand and the MODWT is applied to these series. Moreover, the banking sector indices are calculated as an equally-weighted average instead of applying the weighting scheme in Table 2.1. The resulting network statistics show that the results are not sensitive to the alternative specifications.

2.4 Conclusion

This study specifies directed and dependence-weighted networks of sovereign and bank risk contagion for different time horizons over the period 2009–2021. By applying Maximal Overlap Discrete Wavelet Transformation, daily CDS premia of sovereigns and systemically important eurozone banks are decomposed into multi-horizon components, capturing a time horizon of up to half a year. The network statistics indicate lower connectivity in the short run, while the center of the network is characterized by financially fragile banks. Considering three sub-samples, the short-run and medium-run connectivity of the network reduces after the implementation of the European Banking Union in 2014. However, the null hypothesis of network similarity cannot be rejected in the long run, but the strength of the dependence is significantly reduced across all time horizons. These findings provide important implications for the transmission of sovereign-bank risk. Economically, sovereigns and banks are indirectly connected through the domestic economy. Some studies demonstrate that the economy is likely to suffer from poorer public services, higher taxation, increasing cost of capital, and deterioration of bank asset quality if the sovereign creditworthiness declines. These linkages are likely to persist in the long run. Nevertheless, a shock in sovereign or bank risk is less severely transmitted to other countries in the eurozone due to lower volatility spillovers. This highlights that the introduction of the European Banking Union effectively supports financial stability by weakening the strength of dependence rather than eliminating the dependence itself. Following this argument, the COVID-19 pandemic increased the density of the network through the purchase of sovereign debt securities by eurozone banks, while the strength of the dependence was almost not affected. In order to address the persisting home bias in bank sovereign debt holdings, the European Union should explicitly introduce disincentives against highly concentrated sovereign exposures. This may also reduce the long-run connectivity of the network. Overall, the study also highlights the informational gain of applying time-frequency analysis to evaluate risk dependencies between sovereigns and banks.

2.5 Appendix

Variable	Description
$STOXX$	STOXX Europe 600 stock market index
$MSCI$	MSCI world stock market index
$VSTOXX$	Implied volatility on STOXX Europe 50
VIX	Implied volatility on S&P500
$iTraxx$	European credit default swap index
$iTraxx_c$	European crossover credit default swap index
$iTraxx_s$	iTraxx senior financial credit default swap index
$Eonia$	Euro overnight interest average rate
$Spread$	1-month Euribor – Eonia interest rate
$Risk_{long}$	CITI long-term macroeconomic risk indicator
$Risk_{short}$	CITI short-term macroeconomic risk indicator
TED	Treasury bill eurodollar difference
CDS_{UK}^{bank}	United Kingdom bank CDS index related to Table 2.1
CDS_{UK}^{sov}	United Kingdom sovereign CDS
CDS_{US}^{bank}	United States bank CDS index related to Table 2.1
CDS_{US}^{sov}	United States sovereign CDS

All control variables are considered in log-changes and decomposed into multi-scale components before VAR estimation. Starting on October 2, 2019, the Eonia rate is replaced by €STR + 8.5 basis points.

Table 2.6: Description of the control variables

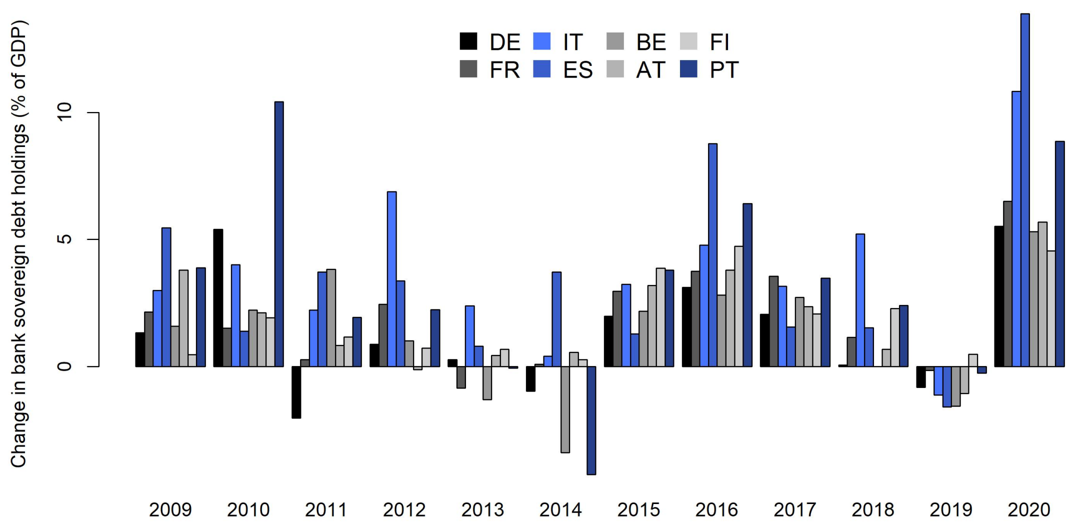

Figure 2.9: Change in government debt held by domestic banks as a percentage of GDP

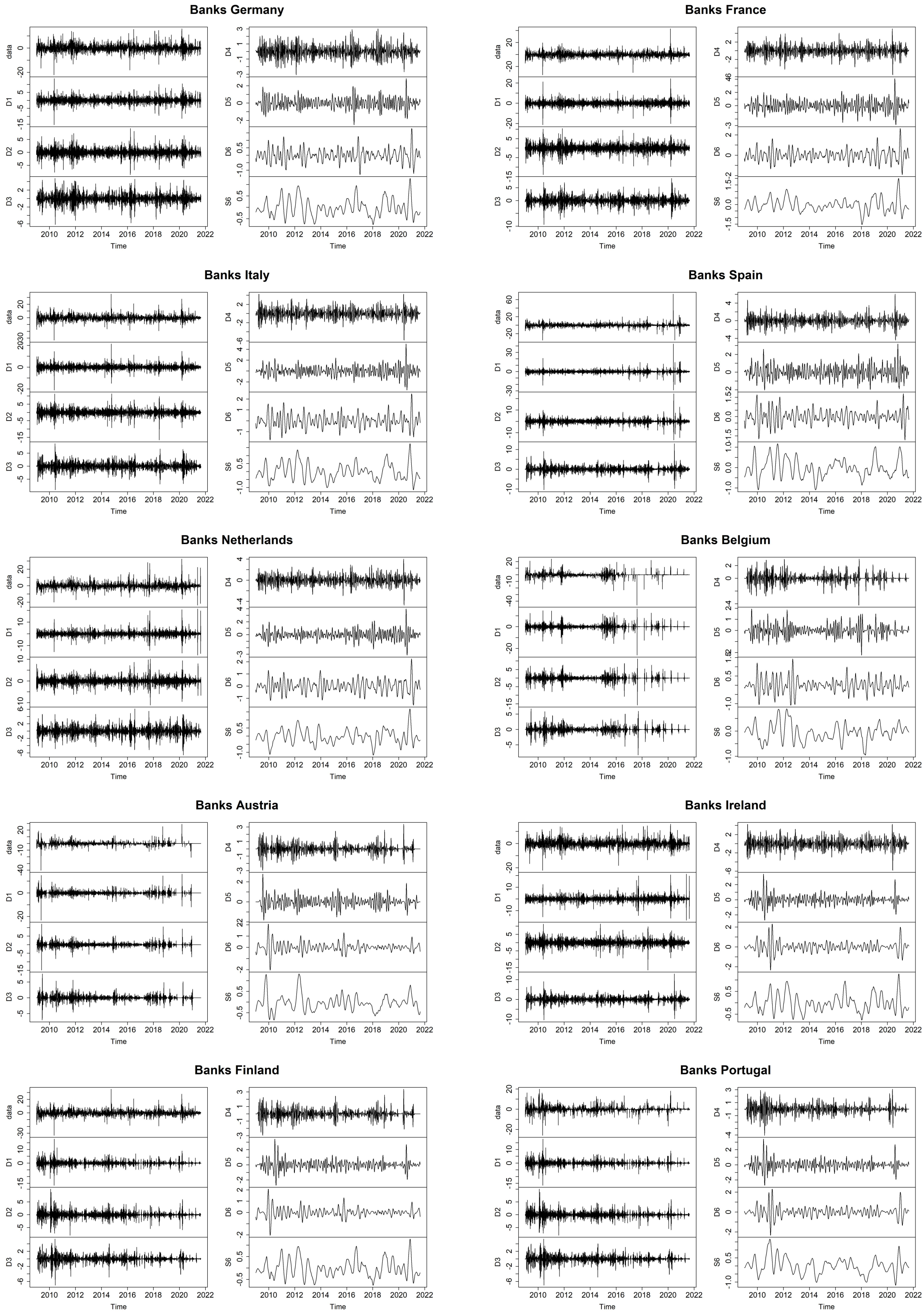

Figure 2.10: Wavelet decomposition of bank CDS

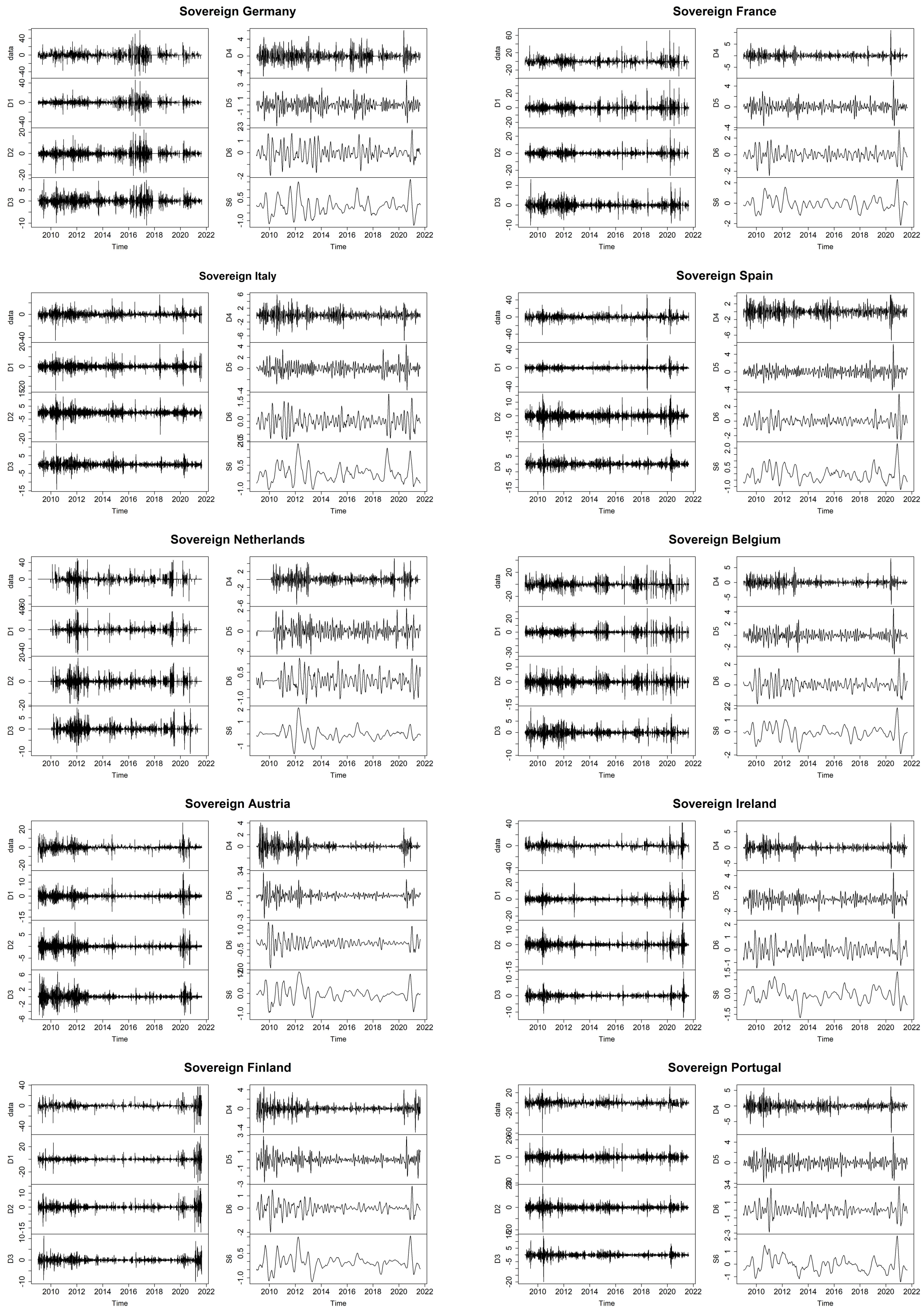

Figure 2.11: Wavelet decomposition of sovereign CDS

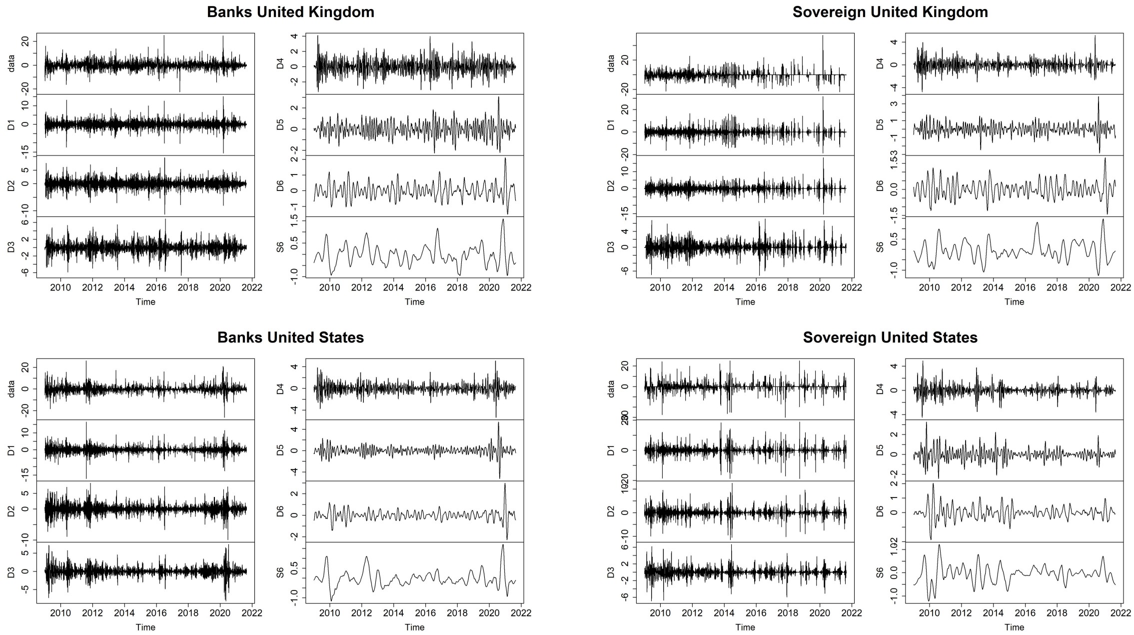

Figure 2.12: Wavelet decomposition of sovereign and bank CDS for the control group

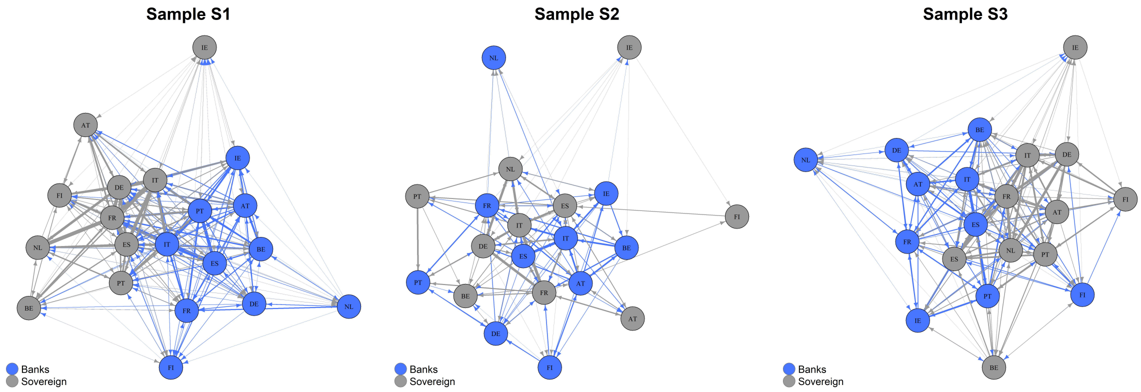

Figure 2.13: Sovereign-bank networks without wavelet decomposition

	$S1$	$S2$	$S3$	*Jaccard similarity*	
Network density	0.66	0.33	0.51	$S1$ & $S2$	0.44
Network reciprocity	0.61	0.43	0.49	$S2$ & $S3$	0.49
Edge strength	0.76	0.30	0.41	$S1$ & $S3$	0.89
Domestic nexus	0.70	0.20	0.50		

Table 2.7: Network statistics without wavelet decomposition

	Mean	Min	Max	SD	Skew	Kurt	Mean	Min	Max	SD	Skew	Kurt
Scale D_1							Scale D_4					
DE	0.00	-15.38	13.65	1.83	0.06	8.31	0.00	-3.10	3.01	0.78	0.13	3.81
FR	0.00	-21.38	24.33	2.49	0.03	12.65	-0.00	-5.58	5.05	1.07	-0.06	4.33
IT	-0.00	-21.10	21.28	2.21	0.08	12.16	-0.00	-5.84	4.26	1.04	-0.04	4.42
ES	-0.00	-28.82	43.10	2.45	0.83	48.78	0.00	-4.44	6.06	0.99	0.18	5.20
NL	0.00	-18.31	21.17	2.23	0.45	18.80	0.00	-4.75	4.02	0.86	-0.03	4.35
BE	-0.00	-26.21	16.28	1.97	-0.67	27.15	0.00	-4.23	3.04	0.69	-0.21	6.77
AT	0.00	-23.18	15.96	1.57	-0.25	31.63	0.00	-2.96	3.38	0.60	0.06	6.10
IE	-0.00	-26.36	32.96	2.65	0.08	34.37	0.00	-4.56	5.21	0.81	0.15	8.12
FI	-0.00	-13.05	15.40	1.43	0.16	24.47	0.00	-1.94	3.37	0.51	0.37	7.19
PT	0.00	-16.47	17.65	1.58	0.04	18.11	0.00	-4.06	3.09	0.71	-0.18	5.93
Scale D_2							Scale D_5					
DE	0.00	-8.67	9.26	1.46	-0.04	6.58	0.00	-2.52	2.83	0.58	0.26	4.81
FR	0.00	-14.04	10.35	1.98	-0.16	6.28	0.00	-2.89	4.07	0.76	0.25	5.14
IT	0.00	-16.65	11.25	1.90	-0.17	7.94	-0.00	-3.52	4.99	0.82	0.33	6.05
ES	0.00	-16.42	24.22	1.91	0.20	17.67	0.00	-2.03	3.18	0.68	0.27	3.98
NL	0.00	-11.16	10.21	1.57	0.05	7.89	0.00	-3.16	3.98	0.67	0.25	6.81
BE	0.00	-15.82	11.20	1.38	-0.49	17.61	0.00	-2.24	1.94	0.46	0.23	5.26
AT	0.00	-14.93	12.10	1.19	-0.09	22.63	0.00	-1.84	2.78	0.47	0.44	6.04
IE	-0.00	-15.85	19.95	1.73	0.17	25.35	0.00	-1.86	2.67	0.47	0.28	6.66
FI	-0.00	-7.72	8.11	0.99	-0.29	13.86	0.00	-1.75	2.12	0.40	0.22	5.84
PT	-0.00	-8.06	10.01	1.15	0.04	11.66	0.00	-2.71	3.40	0.56	0.53	8.87
Scale D_3							Scale D_6					
DE	0.00	-6.17	4.76	1.16	-0.13	5.19	0.00	-1.31	1.80	0.40	0.34	4.88
FR	0.00	-9.38	8.64	1.62	-0.09	5.31	0.00	-1.92	2.62	0.54	0.37	5.15
IT	0.00	-9.12	8.63	1.52	-0.14	5.63	0.00	-1.82	1.77	0.50	0.05	4.26
ES	0.00	-10.49	12.89	1.47	0.02	9.64	-0.00	-1.76	2.48	0.58	0.35	4.23
NL	0.00	-6.61	6.11	1.24	-0.10	5.17	0.00	-1.57	2.24	0.49	0.20	4.29
BE	0.00	-8.32	6.69	0.97	-0.22	12.19	0.00	-1.08	1.43	0.36	0.18	4.37
AT	0.00	-7.04	7.56	0.88	0.16	12.41	0.00	-2.04	2.08	0.39	0.26	8.92
IE	0.00	-7.44	10.59	1.11	0.06	13.39	0.00	-2.29	1.91	0.48	0.04	6.65
FI	0.00	-4.68	6.10	0.70	0.40	12.50	0.00	-1.24	1.24	0.29	0.16	5.81
PT	0.00	-7.04	5.27	0.90	-0.48	8.88	-0.00	-2.35	2.31	0.48	0.37	7.71

This table reports descriptive statistics of sovereign CDS. *'Mean'* depicts the average change in CDS premia, where *'Min'* and *'Max'* indicate the lowest and highest change in CDS premia. *'SD'*, *'Skew'*, and *'Kurt'* provide information about the standard deviation, skewness, and kurtosis of the distribution of CDS changes.

Table 2.8: Descriptive statistics of sovereign CDS by country and scale

	Mean	Min	Max	SD	Skew	Kurt	Mean	Min	Max	SD	Skew	Kurt
Scale D_1							Scale D_4					
DE	-0.00	-48.69	46.38	4.58	0.01	20.53	0.00	-4.77	6.11	1.19	0.22	4.97
FR	0.00	-24.90	38.01	3.75	0.61	14.62	0.00	-8.84	10.91	1.24	0.27	11.96
IT	0.00	-24.11	22.69	2.78	-0.05	12.52	0.00	-7.34	5.96	1.22	-0.20	6.23
ES	0.00	-47.78	50.49	3.67	0.13	47.31	0.00	-7.37	4.38	1.22	-0.20	5.24
NL	-0.00	-48.69	46.38	4.58	0.01	20.53	0.00	-4.77	6.11	1.19	0.22	4.97
BE	-0.00	-32.85	35.34	3.71	-0.37	17.52	0.00	-7.48	8.12	1.10	0.19	10.40
AT	0.00	-15.92	16.97	1.78	0.11	18.73	0.00	-3.81	4.06	0.75	0.03	9.17
IE	0.00	-22.87	31.98	2.71	0.25	25.61	0.00	-6.65	7.86	1.06	0.17	11.07
FI	-0.00	-36.79	36.36	3.22	-0.35	40.15	0.00	-5.12	4.67	0.86	0.02	9.33
PT	0.00	-29.34	23.98	2.61	-0.26	15.29	0.00	-8.53	6.23	1.20	-0.35	9.03
Scale D_2							Scale D_5					
DE	0.00	-20.70	22.35	2.98	0.06	11.58	0.00	-3.09	3.70	0.75	-0.03	5.00
FR	-0.00	-26.42	27.61	2.54	0.21	16.83	0.00	-3.68	5.17	0.83	0.22	7.65
IT	-0.00	-21.06	14.40	2.20	-0.22	10.34	0.00	-3.93	4.37	0.84	0.31	5.58
ES	0.00	-17.68	16.01	2.44	-0.05	9.81	-0.00	-4.19	6.26	0.88	0.46	8.58
NL	0.00	-20.70	22.35	2.98	0.06	11.58	0.00	-3.09	3.70	0.75	-0.03	5.00
BE	0.00	-14.81	15.99	2.35	-0.10	7.68	0.00	-3.25	4.64	0.72	0.36	7.85
AT	0.00	-9.22	10.32	1.31	-0.16	11.81	0.00	-3.11	3.17	0.52	0.15	9.99
IE	0.00	-15.82	15.24	1.86	-0.11	15.24	0.00	-3.15	4.52	0.71	0.19	7.63
FI	-0.00	-18.01	15.05	1.86	-0.39	20.77	0.00	-2.78	2.89	0.54	0.11	8.44
PT	0.00	-22.16	19.05	2.10	-0.18	14.10	0.00	-3.84	5.13	0.89	0.13	6.47
Scale D_3							Scale D_6					
DE	0.00	-11.00	9.72	1.85	-0.00	6.94	0.00	-1.95	1.96	0.58	0.22	3.91
FR	0.00	-10.21	13.02	1.77	0.26	8.51	0.00	-2.52	3.00	0.60	0.18	5.88
IT	0.00	-14.33	11.97	1.69	-0.23	8.28	0.00	-1.43	2.08	0.52	0.29	4.24
ES	0.00	-16.45	13.16	1.80	-0.28	9.48	0.00	-2.59	3.73	0.65	0.44	8.14
NL	0.00	-11.00	9.72	1.85	-0.00	6.94	0.00	-1.95	1.96	0.58	0.22	3.91
BE	0.00	-9.36	10.90	1.57	-0.05	8.06	0.00	-1.86	2.61	0.53	0.34	5.72
AT	-0.00	-5.70	6.77	1.03	0.07	9.60	0.00	-1.88	1.60	0.36	0.08	8.43
IE	0.00	-13.51	14.69	1.47	-0.11	18.10	0.00	-1.44	2.18	0.47	0.49	4.71
FI	0.00	-10.18	11.23	1.23	-0.16	14.23	0.00	-1.99	1.81	0.41	0.03	6.40
PT	0.00	-20.01	14.16	1.71	-0.52	18.78	0.00	-2.89	3.16	0.65	0.32	7.07

This table reports descriptive statistics of bank CDS indices. *'Mean'* depicts the average change in CDS premia, where *'Min'* and *'Max'* indicate the lowest and highest change in CDS premia. *'SD'*, *'Skew'*, and *'Kurt'* provide information about the standard deviation, skewness, and kurtosis of the distribution of CDS changes.

Table 2.9: Descriptive statistics of bank CDS indices by country and scale

Principal Component Analysis

Let $\mathbf{D} = (D_1, \ldots, D_k)'$ denote a vector of wavelet components of k different sovereigns and banks resulting from Equation (2.2) with covariance matrix $\boldsymbol{\Omega_D}$. Principal Component Analysis utilizes a few linear combinations of D_i to explain the overall structure of sovereign and bank contagion in $\boldsymbol{\Omega_D}$. The linear combination of wavelet factors is given by

$$y_i = \boldsymbol{c_i'D} = \sum_{j=1}^{k} c_{ij} D_j, \tag{2.12}$$

where $\boldsymbol{c_i} = (c_{i1},\ldots,c_{ik})'$ is a k-dimensional weighting vector with $i = 1,\ldots,k$. The linear combinations are specified such that y_i and y_j are uncorrelated for $i \neq j$ and the variances of y_i are as large as possible (Tsay, 2010). The variance of the *ith* principal component corresponds to its eigenvalue

$$Var(y_i) = \boldsymbol{c_i'\Omega_D c_i} = \lambda_i. \tag{2.13}$$

Finally, the proportion of total variance in $\mathbf{D}$, i.e. the joint variation in sovereign and bank risk, described by the *ith* principal component is calculated as

$$\frac{Var(y_i)}{\sum_{i=1}^{k} Var(D_i)} = \frac{\lambda_i}{\lambda_1 + \cdots + \lambda_k}. \tag{2.14}$$

In the literature, the *first* principal component is often interpreted as a systemic risk factor for a specific country or sector (Ballester et al., 2016; Abdi and Williams, 2010).

Chapter 3

Policy uncertainty, interest rate environment and the dynamic correlation between sovereign and bank default risk

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Abstract

This study assesses the impact of policy uncertainty and the interest rate environment on the sovereign-bank nexus, considering 48 banks in 14 countries. By applying principal component analysis to bank CDS premia in a country, the dynamic conditional correlation between sovereign CDS premia and the common variation underlying bank CDS is specified. Fixed effects panel regression analysis shows that the sovereign-bank correlation significantly increases in times of great policy uncertainty, low bank interest margins, high interbank market rates, and a low ratio of bank Tier 1 capital.

Keywords: Sovereign-bank nexus, policy uncertainty, interest rates, DCC-GARCH.

*The non-commercial use of this study is permitted by Elsevier as part of my dissertation. DOI: 10.1016/j.econlet.2021.109983, © 2021 Elsevier. Minor modifications have been made in terms of labels, expressions, and the appendix to ensure consistency and comprehensibility within the thesis.

3.1 Introduction and related literature

Uncertainty about political actions affects the behavior of businesses, households, and financial intermediaries. Since the level of policy uncertainty is not directly observable, different proxies are considered in the literature. Some studies employ national election events, whereas others use (macroeconomic) indicators like volatility indices, news-based uncertainty, or forecast disagreement to measure the level of policy uncertainty. Selmi and Bouoiyour (2020) examine the effect of the 2016's U.S. presidential election on the stock market. Using event study methods, they find a negative impact on stock returns. The studies of Francis et al. (2014), Naifar et al. (2018), and Bordo et al. (2016) demonstrate that policy uncertainty is an important risk factor for banks and a firm's idiosyncratic exposure to policy uncertainty is significantly associated with the cost of bank loans in the United States. Moreover, Wang et al. (2018) and Wisniewski and Lambe (2015) show that the economic policy uncertainty (EPU) index of Baker et al. (2016) Granger causes corporate CDS spreads in the U.S. and Europe. The same influence is observed for sovereign CDS. Examining bank default risk in emerging economies, Wu et al. (2020) conclude that bank default risk significantly increases with higher levels of economic uncertainty. Pástor and Veronesi (2013) develop a general equilibrium model of government policy choice where stock prices respond to political news. They show that policy uncertainty commands a risk premium and increases the correlation between stocks.

However, the literature falls short to analyze the impact of policy uncertainty on the two-way interdependence between the default risk of governments and banks, called the sovereign-bank nexus. The connection is a possible transmission mechanism by which sovereign market stress may become systemic (Garcia de Andoain and Kremer, 2017). By investing in domestic government bonds, banks are able to earn the entire risk premium, while the risk itself is mainly borne by their creditors (Andreeva and Vlassopoulos, 2019). This provides an incentive to invest in domestic sovereign debt, which is often designated as a "home bias" in bank debt portfolios. In principle, linkages between banks and sovereigns can take multiple forms; direct or indirect. Direct linkages from banks to sovereigns include guarantees of banks' equity and liabilities or government ownership. Direct links from sovereigns to banks comprise any claims of the banks on the sovereign, such as sovereign debt holdings (Altavilla et al., 2017). In addition, heavy indirect linkages exist through the domestic economy. Some studies argue that banks could turn out as the main channel through which EPU is transmitted to the real economy (Bordo et al., 2016; Nguyen et al., 2020). In addition, Heider et al. (2019) claim that the development of interest rates in the eurozone led to more bank risk-taking and higher bank CDS premia.

Assuming that bank risk can be transmitted to the sovereign and vice versa, this implies an impact on the sovereign-bank nexus. This study contributes to prior research of Bales (2022*a*) by examining the impact of interest rates and policy uncertainty on the dynamic sovereign-bank correlation in 14 developed countries. The results indicate considerable heterogeneity between eurozone and non-eurozone banks and reveal a tightening of the nexus in times of great policy uncertainty, low bank interest margins, high interbank market rates, and low Tier 1 capital. In the following, Section 3.2 describes the methods, while Section 3.3 presents the estimation results. Finally, Section 3.4 reaches a conclusion.

3.2 Data and methodology

The analysis considers daily 5-year Credit Default Swap premia from January 1, 2010, to March 31, 2021. A Credit Default Swap (CDS) works like an insurance contract against default, where the premium is considered as a proxy for the default risk. All CDS are senior unsecured claims with a modified restructuring clause collected from Thomson Reuters Eikon. CDS contracts with a length of 5 years are used, as these are the most liquid and actively traded contracts (Bruyckere et al., 2013). In each country, at least two banks are selected to measure the common variation underlying individual bank default risk. Overall, the sample comprises 25 eurozone and 23 non-eurozone banks (Table 3.1).

3.2.1 Principal component analysis

Following Ballester et al. (2016), Principal Component Analysis (PCA) is applied to the banks listed in Table 3.1 to extract the common source of bank CDS premia variation in a country. Let $\boldsymbol{x_j} = (\Delta CDS^{bank}_{1,j}, \ldots, \Delta CDS^{bank}_{p,j})$ denote a vector of daily CDS premia changes of p banks in country j with covariance matrix $\boldsymbol{\Omega_j}$. PCA utilizes a few linear combinations of $\Delta CDS^{bank}_{i,j}$ to explain the structure of $\boldsymbol{\Omega_j}$. Following Kaiser (1961), the optimal number of components is defined by the number of eigenvalues that exceed one. An eigenvalue of $\lambda_i = 1$ states that the principal component contains the same amount of information as the CDS premium itself. The *first* principal component in a country is given by a combination of CDS premia as

$$Y^{bank}_{1,j} = a_{11}\Delta CDS^{bank}_{1,j} + \cdots + a_{1p}\Delta CDS^{bank}_{p,j}, \tag{3.1}$$

where the weights $a_{11}, \ldots, a_{1p}$ are chosen such that $\text{Var}(Y^{bank}_{1,j})$ is maximized and the condition $a^2_{11} + \ldots + a^2_{1p} = 1$ applies. After maximization, time-varying component scores,

j	Bank p
Eurozone (E)	
IT	UniCredit, Intesa Sanpaolo, Mediobanca, Banca Monte dei Paschi di Siena, Banca Nazionale del Lavoro
ES	Banco Santander, Banco Bilbao Vizcaya Argentaria, Banco Sabadell, Bankinter
FR	BNP Paribas, Crédit Agricole, Société Générale, Le Crédit Lyonnais
DE	Deutsche Bank, Commerzbank, Landesbank Baden-Wuerttemberg, BayernLB
NL	ING-DiBa, Rabobank
PT	Banco Comercial Português, Caixa Geral de Depósitos
AT	Erste Group Bank, BAWAG P.S.K.
IE	Allied Irish Banks, Bank of Ireland
Non-eurozone (N)	
US	J.P. Morgan, Bank of America, Citigroup, Wells Fargo, Capital One, Morgan Stanley
UK	HSBC, Barclays, Lloyds Banking Group, Standard Chartered Bank
JP	Mizuho Financial, Sumitomo Mitsui Banking Corporation, Mitsubishi UFJ
AU	CMWL Bank of Australia, National Bank of Australia, ANZ Bank, Westpac
SW	Skandinaviska Enskilda Banken, Svenska Handelsbanken, Swedbank, Nordea
DK	Danske Bank A/S, Jyske Bank A/S

The country codes are as follows: IT: Italy, ES: Spain, FR: France, DE: Germany, NL: Netherlands, PT: Portugal, AT: Austria, IE: Ireland, US: United States, UK: United Kingdom, JP: Japan, AU: Australia, SW: Sweden, DK: Denmark.

Table 3.1: Description of banks in the sample

$Score^{bank}_{1,j,t}$, are obtained from sample predictions of Equation (3.1). These scores capture the *joint* banking sector risk in a country (Tsay, 2010; Brooks, 2008). Finally, the proportion of overall variance in $\boldsymbol{x_j}$ described by the first principal is given by

$$P_{1,j} = \frac{Var(Y^{bank}_{1,j})}{\sum_{i=1}^{p} Var(\Delta CDS^{bank}_{i,j})} = \frac{\lambda_1}{\lambda_1 + \cdots + \lambda_p}, \tag{3.2}$$

where the variance of the first principal component is equal to its eigenvalue λ_1.

3.2.2 Dynamic sovereign-bank correlation

To address the correlation between sovereign and bank default risk, the Dynamic Conditional Correlation (DCC) model of Engle (2002) is applied. Unlike alternative correlation measures, the DCC methodology controls for heteroscedasticity. This is of crucial importance since the sovereign-bank correlation increases in turbulent times due to the rise in volatility associated with those periods (Buchholz and Tonzer, 2016). The mean dependence is specified by a bivariate Vector AutoRegressive (VAR) Model

$$\Delta CDS_{j,t} = \mu_j + \sum_{k=1} \Gamma_{k,j} \Delta CDS_{j,t-k} + \upsilon_{j,t}, \tag{3.3}$$

where $\Delta CDS_{j,t} = [\Delta CDS_{j,t}^{sov}, Score_{1,j,t}^{bank}]'$ is a vector of sovereign CDS premia changes and the first principal component scores of bank CDS in a country obtained from Equation (3.1). Moreover, μ_j defines a vector of constants and $\Gamma_{1,j}, \ldots, \Gamma_{k,j}$ denote the autoregressive coefficient matrices. The lag length k is chosen according to the information criterion of Akaike (1974). A detailed description of the method is included in the Appendix. In the DCC model, the residuals of Equation (3.3) are distributed as $\upsilon_{j,t} \sim N(0, H_{j,t})$ with

$$H_{j,t} = D_{j,t} R_{j,t} D_{j,t}. \tag{3.4}$$

$R_{j,t}$ represents a 2×2 conditional correlation matrix and $D_{j,t} = diag\{\sqrt{h_{j,t}}\ \}$ contains conditional standard deviations obtained from a univariate GARCH(1,1) process

$$h_{j,t} = \alpha_{0,j} + \alpha_{1,j} \upsilon_{j,t-1}^2 + \beta_j h_{j,t-1}. \tag{3.5}$$

The conditional 2×2 variance-covariance matrix $Q_{j,t}$ is computed as

$$Q_{j,t} = (1 - \alpha_j - \beta_j)\overline{Q}_j + \alpha(z_{j,t-1} z_{j,t-1}') + \beta_j Q_{j,t-1}, \tag{3.6}$$

where $\overline{Q}_j$ depicts a time-constant correlation matrix and $z_{j,t} = \upsilon_{j,t}/\sqrt{h_{j,t}}$ are standardized residuals. The time-varying sovereign-bank correlation is finally defined as

$$R_{j,t} = diag(Q_{j,t})^{-1/2}\ Q_{j,t}\ diag(Q_{j,t})^{-1/2} = \begin{bmatrix} 1 & r_{j,t} \\ r_{j,t} & 1 \end{bmatrix}. \tag{3.7}$$

To estimate the unknown coefficients, the log-likelihood function is given by

$$\begin{aligned} L = &\left[-1/2 \sum_t (2log(2\pi) + log|D_{j,t}|^2 + \upsilon_{j,t}' D_{j,t}^{-2} \upsilon_{j,t})\right] \\ &+ \left[-1/2 \sum_t (log|R_{j,t}| + z_{j,t}' R_{j,t}^{-1} z_{j,t} - z_{j,t}' z_{j,t})\right], \end{aligned} \tag{3.8}$$

where the first bracketed term represents the volatility and the second term the correlation component. First, the volatility part is maximized to obtain estimates for Equation (3.5). Based on these values, the correlation part is maximized with respect to the remaining parameters of the correlation matrix $R_{j,t}$ (Engle, 2002). Overall, this yields estimates of the time-varying sovereign-bank dependence for the 14 countries in the sample.

3.3 Results and discussion

Table 3.2 reports the proportion of overall variation in bank default risk described by the first principal component. In all countries, $Y_{1,j}^{bank}$ describes about 50%–80% of the total CDS premia variation. This indicates a significant common driver of domestic bank default risk, likely stemming from equal conditions for banks within the same country.

j	IT	ES	FR	DE	US	UK	JP	SW	IE	PT	AU	AT	NL	DK
$P_{1,j}$	0.57	0.69	0.80	0.49	0.73	0.63	0.53	0.61	0.67	0.74	0.67	0.57	0.73	0.64

Table 3.2: Proportion of bank CDS variation explained by the first principal component

Considering the DCC-GARCH estimates, Figure 3.1 shows heterogeneity in the time-average sovereign-bank correlation. The circles depict the variation over time. The smallest correlations are observable in Sweden, Denmark, and the United States. In contrast, financially fragile eurozone members, such as Italy, Spain, and Portugal, exhibit the highest dependence between bank and sovereign default risk. In Austria, the Netherlands, and the U.S., the correlations are only slightly changing over time.

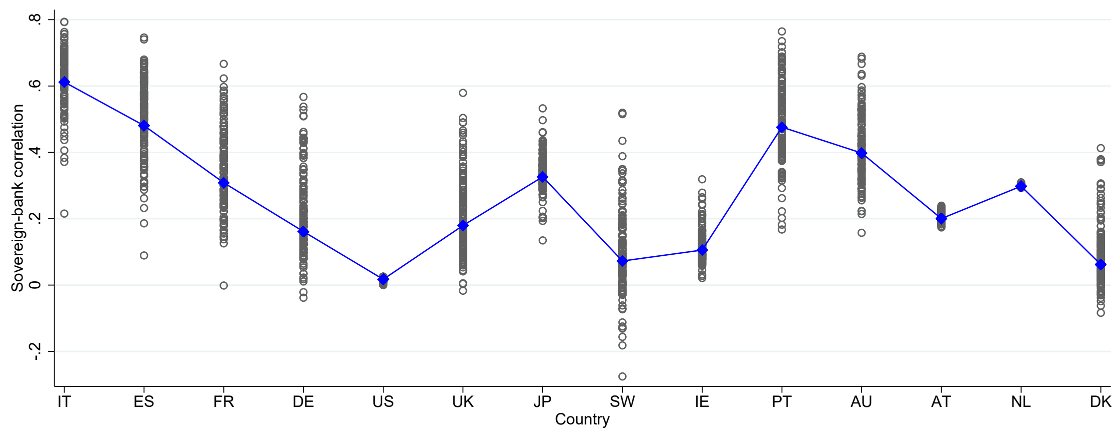

Figure 3.1: Sovereign-bank correlation: Heterogeneity across countries

Moreover, Figure 3.2 compares the correlation development of eurozone and non-eurozone member states over time. The figure reveals that the sovereign-bank default risk dependence is significantly higher in the eurozone. These findings are in line with 2018's EBA stress testing exercise, where European banks exhibited a strong home bias in their debt portfolio. A further explanation is provided by the risk-shifting hypothesis. Uhlig (2014) argues that the European Monetary Union implicitly shifts sovereign default risk onto the balance sheet of the European Central Bank and the rest of the Eurosystem by delivering underpriced loans from banks to their sovereigns. As a result, the sovereign-bank dependence in the eurozone countries is amplified by cross-country contagion. This leads to the observation that the dependence in non-eurozone countries decreased after the financial crises (2012–2014), while the correlation in the euro area remained high. All individual correlations are plotted in Figure 3.3 in the Appendix.

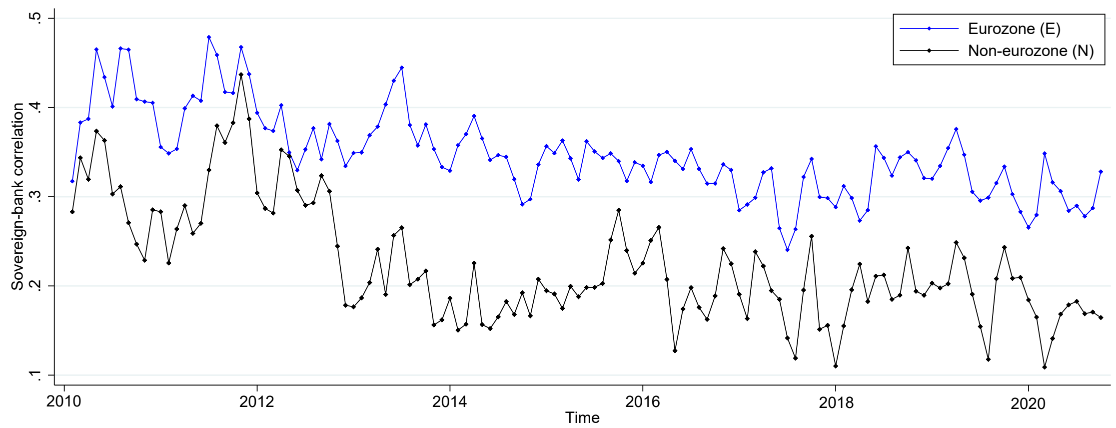

Figure 3.2: Sovereign-bank correlation: Heterogeneity across time

3.3.1 Determinants of the dynamic sovereign-bank correlation

To characterize driving factors of the default risk relationship, the monthly[1] correlation is examined using fixed effects panel regression of the form

$$\Delta r_{j,t} = \beta_1 \Delta Explanatory_{j,t} + \beta_2 \Delta Control_{j,t} + \alpha_j + \lambda_t + \epsilon_{j,t}, \tag{3.9}$$

where α_j and λ_t capture country and time fixed effects respectively. $Explanatory_{j,t}$ relates to a vector of risk measures, regulatory variables, and policy uncertainty indicators. A detailed explanation of all explanatory and control variables is provided in Table 3.3.

[1]Daily CDS are initially used to obtain reliable estimates i.e. $N \geq 500$ (Hwang and Pereira, 2006).

Variable	Description	Source	Area	Freq.
Explanatory				
EPU_C	Domestic economic policy uncertainty, index value	Baker	C	M
EPU_E	European economic policy uncertainty, index value	Baker	E	M
EPU_W	Global economic policy uncertainty, index value	Baker	W	M
EPU_M	Monetary policy uncertainty, index value	Baker	US	M
Spread	1-month Euribor – Eonia interest rate, percentage value	ECB	E	M
Margin	Lending margin on new loans to households and non-financial corporations: Interest on new loans – weighted average of interest on new deposits, country-average	ECB	C	M
Assetrisk	Share of variable rate bank loans to total new business loans, country-average	ECB	C	M
Yieldcurve	Datastream government bond yield curve, constant maturity of 5 years, percentage value	Eikon	C	M
Interbank	3-month average interbank market rate, percentage value	OECD	C	M
Tier1	Ratio of regulatory Tier 1 capital to total risk-weighted assets, country-average	IMF	C	Q
Msupply	Growth rate of money supply M3 in the eurozone, seasonally adjusted, percentage rate	ECB	E	M
Control				
Volatility	VSTOXX, VIX, FTSE Vola, NIKKEI Vola, ASX Vola (AU)	Eikon	C/E	M
Stock	FTSE MIB (IT), IBEX35 (ES), CAC40 (FR), DAX30 (DE), NASDAQ (US), FTSE100 (UK), NIKKEI225 (JP), OMX30 (SW), ISEQ (IE), PSI20 (PT), ASX200 (AU), ATX (AT), AEX (NL), OMXC20 (DK), index value	Eikon	C	M
MSCI	MSCI world stock market index, index value	Eikon	W	M
UR	Unemployment rate, International Labor Organization, seasonally adjusted, percentage	Eikon	C	M
IP	Level of industrial production/output, index value	Eikon	C	M
Sent	Consumer sentiment index (CSI), University of Michigan surveys, index value	UMich	C	M
ULC	Unit labor costs (productivity), seasonally adjusted, index value, 2010 = 100	OECD	C	Q
GDP	Gross Domestic Product, millions of euro	OECD	C	Q
Wage	Hourly wage rate, all industries and workers, value	Eikon	C	M
Hours	Hours worked per employee, seasonally adjusted, index value	OECD	C	M
Debt	Outstanding government debt securities, millions of euro	Eikon	C	M
Inf	Inflation rate, monthly change of consumer price index, percentage value	Eikon	C	M

C: Country-specific, E: Eurozone-specific, W: Worldwide, M: Monthly, Q: Quarterly.

Table 3.3: Description of the independent variables

As first explanatory variables, news-based economic policy uncertainty indices of Baker et al. (2016) are employed to capture domestic, global, European, and monetary policy uncertainty respectively. Second, bank lending margins are calculated as the average difference between interest on new business loans and a weighted average of the interest rate on new deposits in a country. Third, domestic bond market conditions are covered by the slope of the yield curve, assuming a constant maturity of 5 years. Fourth, the average share of variable rate bank loans to total new business loans in a country is considered as a bank risk indicator. Moreover, the 3-month average interbank market rate and the ratio of regulatory Tier 1 capital to total risk-weighted assets in each country are used to assess the borrowing conditions and healthiness of the banking sector. For the eurozone, the 1-month Euribor-Eonia spread is considered as a barometer of money market distress. In addition, the growth rate of money supply M3 is considered. Finally, macroeconomic control variables (Table 3.3) are included to derive causal effects since different channels of the nexus interact with each other. The standard errors are clustered at the country level and variable changes are considered because of non-stationarity. Due to the possible correlation between the explanatory variables, the model is estimated in various specifications.

Considering the regression results in Table 3.4, the sovereign-bank correlation increases in times of higher *domestic* policy uncertainty (Model W1). However, the effect becomes statistically insignificant if the level of *global* EPU is taken into account (Model W2). This highlights the relevance of worldwide policy uncertainty. In the eurozone, European rather than global or domestic policy uncertainty affects the default risk dependence. In line with prior results, this reveals the importance of policy risk spillovers within the monetary union (Model E1). Looking at the United States allows to specifically define the source of policy uncertainty. In general, the overall level of policy uncertainty is affected by the actions of the government and the central bank (Tillmann, 2019). While the levels of global and overall domestic EPU do not affect the nexus, the sub-index of monetary policy uncertainty does (Model US). Economically, uncertainty about policies or interest rates causes households and firms to postpone their investments, which encourages bank-risk taking and is likely to enhance sovereign and firm credit risk (Liu and Zhong, 2017; Berger et al., 2017). In line with Wisniewski and Lambe (2015) and Wang et al. (2018), who claim EPU to be an important determinant of firm CDS premia, the present results show that (monetary) policy uncertainty is also important in explaining the sovereign-bank dependence.

In addition to uncertainty, the vulnerability of the financial system impacts the strength of the dependence between sovereign and bank default risk. Banks with a low level of core equity capital relative to their total risk-weighted assets are less likely to withstand shocks to their balance sheets. The higher default risk of a poorly capitalized banking system spills over to the state, resulting in a greater risk dependence. This finding extends prior research of Bruyckere et al. (2013) about its applicability to a wider range of (non-eurozone) countries and a period after the European debt crisis. The Tier 1 effect remains significant if global EPU is taken into consideration (Model W3). This emphasizes the importance of both, policy uncertainty and regulatory capital requirements. In addition, higher interbank market rates are associated with a significant tightening of the linkage (Model W4). In times of financial distress, banks charge each other higher rates for unsecured short-term lending. In this way, bank liquidity issues and lending aversion in the interbank market are passed on to other domestic banks and ultimately to the sovereign. A similar effect is observable for the eurozone-specific risk barometer, the Euribor-Eonia spread. While the Eonia has little exposure to default risk, the Euribor reflects credit and liquidity risk (Sengupta and Tam, 2008). The overnight rate usually marks the first step in the monetary policy transmission process. If banks charge higher lending rates, the Euribor–Eonia spread widens and the dynamic sovereign-bank dependence raises (Model E2). Finally, the correlation increases in times of low bank profitability conditions (Model W5). In contrast, the slope of the yield curve, the growth rate of the monetary base in the eurozone, and the ratio of variable bank loans to overall loans are not important for explaining the sovereign-bank nexus since these variables are statistically insignificant (Model W6 and Model E3).

3.3.2 Robustness of the results

To assess the methodological fit of the estimated correlations, the distribution of the standardized residuals is evaluated. In line with the distributional assumption underlying GARCH models, the residuals follow a normal distribution. Thus, the methodology appropriately captures the non-linearity in the default risk variance. Second, Equation (3.3) is specified as a univariate rather than multivariate VAR process. In this way, the sovereign-bank relation is solely captured by the dependence in volatility. The resulting estimated correlations are not sensitive to different mean specifications. Finally, dynamic correlations are estimated based on sovereign and bank CDS indices. In contrast to individual bank data, the indices incorporate over 100 different banks. Again, the resulting estimates and panel regression outcomes do not change the main conclusions of this paper.

Variable	(W1) $\Delta r_{j,t}$	(W2) $\Delta r_{j,t}$	(W3) $\Delta r_{j,t}$	(W4) $\Delta r_{j,t}$	(W5) $\Delta r_{j,t}$	(W6) $\Delta r_{j,t}$	(E1) $\Delta r_{j,t}$	(E2) $\Delta r_{j,t}$	(E3) $\Delta r_{j,t}$	(US) $\Delta r_{j,t}$
ΔEPU_C	0.4823*	0.1814					0.1517			-0.0139
	(0.2385)	(0.3027)					(0.4332)			(0.0327)
ΔEPU_W		1.0810**	0.9868*				-0.4303	-0.7586		-0.0296
		(0.4082)	(0.5141)				(0.5184)	(0.4520)		(0.0530)
$\Delta Tier1$			-3.3724*	-4.4462**						
			(1.6665)	(1.6366)						
$\Delta Interbank$				5.6254**						
				(2.3103)						
$\Delta Margin$					-0.1300*					
					(0.0752)					
$\Delta Yieldcurve$						0.3988				
						(0.3489)				
ΔEPU_E							1.2172**	1.5748**		
							(0.5140)	(0.5979)		
$\Delta Spread$								12.4153**		
								(4.3137)		
$\Delta Assetrisk$									0.0180	
									(0.0149)	
$\Delta Msupply$									0.0219	
									(0.1981)	
ΔEPU_M										0.0998***
										(0.0324)
R^2	0.62	0.64	0.65	0.69	0.63	0.60	0.60	0.64	0.56	0.43
Obs.	1,823	1,823	1,823	1,782	1,823	1,823	1,047	1,047	1,047	121
Countries	14	14	14	14	14	14	8	8	8	1
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Time FE

Standard errors are in parentheses and clustered at the country level. E: Eurozone. W: World (E+N). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.4: Fixed effects panel regression results

3.4 Conclusion

This paper evaluates the influence of policy uncertainty and interest rates on the sovereign-bank nexus. Based on fixed effects panel regression, the sovereign-bank correlation is found to increase in times of great policy uncertainty, high interbank market rates, low bank lending margins, and a low ratio of core bank capital relative to its total risk-weighted assets. The results demonstrate the relevance of political factors and cross-country policy spillovers for the systemic risk in a country. Moreover, the findings emphasize the importance of capital adequacy regulations and joint policies in order to mitigate sovereign-bank dependencies, especially in the eurozone.

3.5 Appendix

The DCC-GARCH model step by step

Multivariate GARCH models account for the volatility dependence between different time series. The main goal is to specify the covariance matrix Q_t, where the subscript t indicates the time-varying characteristic of the matrix. The estimation is conducted in two steps (Engle, 2002). In the first step, sovereign and bank CDS variances are independently modeled using two univariate GARCH(1,1) models

$$Sovereign: \quad h_{1,t}^2 = \alpha_{01} + \alpha_{11}\upsilon_{1,t-1}^2 + \beta_1\sigma_{1,t-1}^2 \tag{3.10}$$

$$Bank: \quad h_{2,t}^2 = \alpha_{02} + \alpha_{12}\upsilon_{2,t-1}^2 + \beta_2\sigma_{2,t-1}^2, \tag{3.11}$$

where α_{0i} depicts a constant, α_{1i} covers the short-run, and β_i the long-run dynamics for $i = \{1,2\}$. Thereafter, a (2×2) diagonal matrix D_t is constructed containing the conditional standard deviations, $h_{1,t}$ and $h_{2,t}$, on the main diagonal. Taking the square root of the variances predicted by Equations (3.10) and (3.11) yields

$$D_t = \begin{bmatrix} h_{1,t} & 0 \\ 0 & h_{2,t} \end{bmatrix}. \tag{3.12}$$

Afterward, the VAR residuals of Equation (3.3) are divided by the conditional standard deviation. In matrix notation, this corresponds to multiplying the residuals with the inverted matrix of D_t as

$$z_t = D_t^{-1}\upsilon_t = \begin{bmatrix} \frac{1}{h_{1,t}} & 0 \\ 0 & \frac{1}{h_{2,t}} \end{bmatrix} \begin{bmatrix} \upsilon_{1,t} \\ \upsilon_{2,t} \end{bmatrix} = \begin{bmatrix} \frac{\upsilon_{1,t}}{h_{1,t}} \\ \frac{\upsilon_{2,t}}{h_{2,t}} \end{bmatrix} = \begin{bmatrix} z_{1,t} \\ z_{2,t} \end{bmatrix}. \tag{3.13}$$

The resulting z_t is a (2×1) vector of *iid* errors. Based on that, the *unconditional* covariance matrix $\overline{Q}$ is calculated by averaging $z_t z_t^T$ over time, yielding

$$\overline{Q} = \frac{1}{T}\sum_{t=1}^{T} \begin{bmatrix} z_{1,t}^2 & z_{1,t}z_{2,t} \\ z_{2,t}z_{1,t} & z_{2,t}^2 \end{bmatrix} = \begin{bmatrix} \overline{\rho}_{1,1} & \overline{\rho}_{1,2} \\ \overline{\rho}_{1,2} & \overline{\rho}_{2,2} \end{bmatrix}. \tag{3.14}$$

In the second step, the dependence between the variables is estimated. Therefore, $\overline{Q}$ is used to compute the *conditional* covariance matrix Q_t by assuming a GARCH(1,1) structure as $Q_t = (1 - \alpha - \beta)\overline{Q} + \alpha(z_{t-1}z_{t-1}') + \beta Q_{t-1}$ (Engle, 2002). The parameters α and β are likewise capturing the short-run and long-run dynamics. The fraction of

$(1-\alpha-\beta)$ refers to the unconditional covariance matrix with $\alpha+\beta<1$ (Martin et al., 2011). The single elements of Q_t, i.e. the conditional variances $q_{1,1,t}$ and $q_{2,2,t}$ as well as the conditional covariance $q_{1,2,t}$, are obtained from

$$\begin{aligned} q_{1,1,t} &= \overline{\rho}_{1,1}(1-\alpha-\beta)+\alpha(z_{1,t-1}z_{1,t-1})+\beta(q_{1,1,t-1}) \\ q_{2,2,t} &= \overline{\rho}_{2,2}(1-\alpha-\beta)+\alpha(z_{2,t-1}z_{2,t-1})+\beta(q_{2,2,t-1}) \\ q_{1,2,t} &= \overline{\rho}_{1,2}(1-\alpha-\beta)+\alpha(z_{1,t-1}z_{2,t-1})+\beta(q_{1,2,t-1}). \end{aligned} \tag{3.15}$$

The resulting matrix Q_t is a function of just two unknown scalar parameters α and β (Martin et al., 2011). Finally, the conditional correlation matrix R_t is calculated as $R_t = diag(Q_t)^{-1/2}\ Q_t\ diag(Q_t)^{-1/2}$. In matrix notation, this yields

$$\begin{aligned} R_t &= \begin{bmatrix} \frac{1}{\sqrt{q_{1,1,t}}} & 0 \\ 0 & \frac{1}{\sqrt{q_{2,2,t}}} \end{bmatrix} \overbrace{\begin{bmatrix} q_{1,1,t} & q_{1,2,t} \\ q_{1,2,t} & q_{2,2,t} \end{bmatrix}}^{Q_t} \begin{bmatrix} \frac{1}{\sqrt{q_{1,1,t}}} & 0 \\ 0 & \frac{1}{\sqrt{q_{2,2,t}}} \end{bmatrix} \\ &= \begin{bmatrix} 1 & \frac{q_{1,2,t}}{\sqrt{q_{1,1,t}q_{2,2,t}}} \\ \frac{q_{1,2,t}}{\sqrt{q_{1,1,t}q_{2,2,t}}} & 1 \end{bmatrix}. \end{aligned} \tag{3.16}$$

By definition, the correlation of a variable with itself is 1. Hence, the main diagonal elements of R_t are accordingly. The off-diagonal elements of the symmetric matrix, $r_t = \frac{q_{1,2,t}}{\sqrt{q_{1,1,t}q_{2,2,t}}}$, define the dynamic conditional correlation between sovereign and bank default risk at time t.

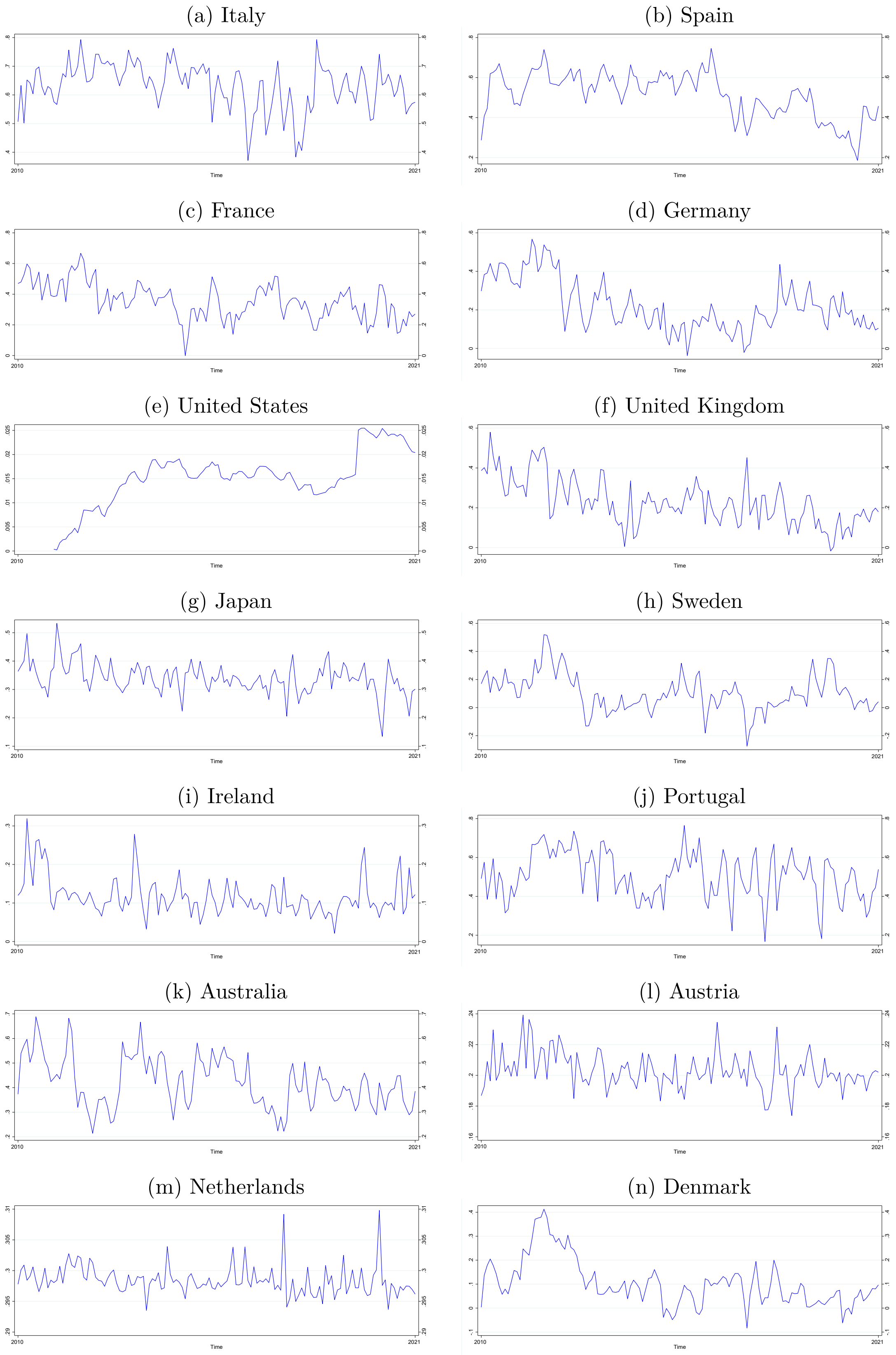

Figure 3.3: Dynamic conditional sovereign-bank correlation by country

j	Mean	Min	Max	SD	Skew	Kurt	Obs
IT	0.63	0.22	0.79	0.09	-1.27	6.11	135
ES	0.51	0.09	0.75	0.12	-0.72	3.35	135
FR	0.36	-0.00	0.67	0.12	0.03	2.90	135
DE	0.22	-0.04	0.57	0.13	0.60	2.63	135
US	0.02	0.00	0.03	0.01	-0.45	3.40	122
UK	0.23	-0.02	0.58	0.12	0.51	2.95	135
JP	0.34	0.13	0.53	0.06	-0.09	5.05	135
SW	0.09	-0.23	0.52	0.16	-0.93	7.24	135
IE	0.12	0.02	0.32	0.05	1.49	5.83	135
AU	0.42	0.16	0.69	0.10	0.23	2.66	135
PT	0.50	0.17	0.76	0.12	-0.32	2.67	135
AT	0.20	0.17	0.24	0.01	0.57	3.80	135
NL	0.30	0.29	0.31	0.00	1.55	8.56	135
DK	0.10	-0.08	0.41	0.10	1.07	4.11	135

This table reports descriptive statistics of the estimated sovereign-bank correlation. *'Mean'* depicts the average correlation, where *'Min'* and *'Max'* indicate the lowest and highest correlation. *'SD'*, *'Skew'*, and *'Kurt'* provide information about the standard deviation, skewness, and kurtosis of the correlation distribution. *'Obs'* indicates the number of DCC estimates.

Table 3.5: Descriptive statistics of the sovereign-bank correlation by country

Chapter 4

Policy uncertainty and the sovereign-bank nexus: A time-frequency analysis using wavelet transformation

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Abstract

This study examines the impact of policy uncertainty on the sovereign-bank nexus over various time scales and frequencies. Considering Credit Default Swap premia of 32 banks in 10 countries, cross-wavelet analysis shows that sovereign default risk leads banking sector default risk in the short run, while the relation reverses in the medium run. Periods of high sovereign-bank dependence, moreover, coincide with periods of great political uncertainty. Applying partial wavelet coherency analysis, the sovereign-bank dependencies significantly weaken once the influence of economic policy uncertainty is eliminated. This demonstrates a significant tightening of the sovereign-bank nexus in times of great policy uncertainty.

Keywords: Sovereign-bank nexus, policy uncertainty, continuous wavelet analysis.

*The non-commercial use of this study is permitted by Elsevier as part of my dissertation. DOI: 10.1016/j.frl.2021.102038, © 2022 Elsevier. Minor modifications have been made in terms of labels, illustrations, and the appendix to ensure consistency and comprehensibility within the thesis.

4.1 Introduction and related literature

Uncertainty about policies affects the behavior of households, businesses, and financial intermediaries. A number of studies demonstrate that increasing levels of economic policy uncertainty (EPU) reduce household expenditures (Aaberge et al., 2017), raise the credit risk of firms (Liu and Zhong, 2017), lower bank liquidity creation (Berger et al., 2017), and decrease bank credit growth (Bordo et al., 2016). However, the literature falls short to analyze the impact of policy uncertainty on the sovereign-bank nexus. The latter describes the two-way interdependence between the default risk of governments and banks, constituting a possible transmission mechanism by which sovereign market stress becomes systemic (Garcia de Andoain and Kremer, 2017). An explanation for the connection is provided by large sovereign bond holdings of domestic banks. In general, heavy sovereign exposures bear risks. A shock in sovereign markets risk weakens the financial sector by eroding the value of government guarantees (Acharya et al., 2014). This, in return, may lead to a further increase in sovereign default risk due to bank bail-outs and governmental bank guarantee schemes (König et al., 2014). Erce (2015) shows that a bank bail-out leads to a significant increase in sovereign default risk, while Covi and Eydam (2020) claim that the risk connection has weakened since the implementation of the Single Supervisory Mechanism in 2014. Using the Dynamic Conditional Correlation model proposed by Engle (2002), Buchholz and Tonzer (2016) also reveal the existence of sovereign default risk dependencies across several European countries. Finally, Stolbov et al. (2018) examine the relationship between economic policy uncertainty and systemic risk for nine European countries, showing that the lead-lag patterns vary considerably across different frequencies.

This study closes a gap in the literature by examining the impact of economic policy uncertainty on the sovereign-bank nexus in a time-frequency analysis. As the relation between sovereign and bank default risk is likely to vary over time and during business cycles, wavelet techniques are effectively able to capture these movements. In this study, continuous wavelet transformation (CWT) is applied to estimate the co-movement between sovereign and bank default risk over time and at different time scales. A wavelet is a function that splits a signal into different components that reflect the evolution through time and at particular frequencies. The decomposition is illustrated in Figure 4.1, where the x-y-space relates to the standard representation of a time series. Additionally, the z-axis captures the frequency dimension $(f_1, f_2, \ldots, f_n)$ introduced by applying wavelet transformation tools.

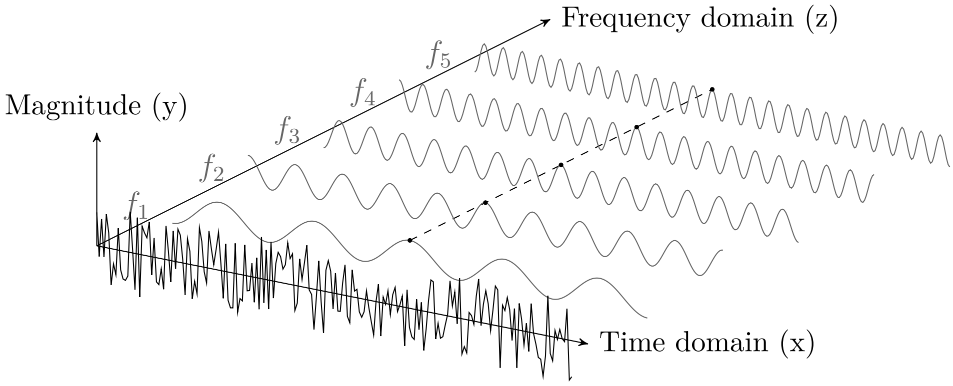


Figure 4.1: Illustration of the time-frequency domain

The continuous wavelet setting also provides a framework to control for exogenous influences, called partial coherency analysis. This allows to examine the importance of economic policy uncertainty on the default risk nexus. The results show heavy sovereign-bank dependencies in times of great policy uncertainty, where greater sovereign risk leads to an increase in banking sector risk in the short run. The causality reverses in the medium run. Once the impact of EPU on sovereign and bank risk is eliminated, the sovereign-bank dependence significantly weakens. The remaining chapter is structured as follows: Section 4.2 introduces the data and methodological background, while Section 4.3 depicts the estimation results. Finally, Section 4.4 reaches a conclusion.

4.2 Data and methodology

This study considers daily 5-year Credit Default Swap premia for a time period from January 1, 2009, to September 1, 2020. A Credit Default Swap (CDS) works like an insurance contract, where the policyholder pays a premium to the insurer to receive compensation for losses arising from default (Bratis et al., 2018). CDS premia are therefore often considered as a proxy for default risk. For the analysis, daily premia are chosen to provide enough observations for obtaining reliable estimates. CDS contracts with a length of 5 years are utilized, as these are the most liquid and actively traded contracts (Bruyckere et al., 2013). All CDS are senior unsecured claims with a modified restructuring clause collected from Thomson Reuters Eikon. Non-trading weekends are excluded from the data sample. To properly capture the banking sector of each country, the banks are selected in line with the definition of local and global systemically important institutions published by the European Banking Authority (EBA) and the Federal Reserve (FED). Overall, the sample comprises 3,048 observations for each sovereign and bank listed in Table 4.1.

j	Bank i
IT	Unicredit, Intesa Sanpaolo, Banca del Lavoro, Banca Monte dei Paschi di Siena
ES	Banco Santander, BBV Argentaria, Banco Sabadell, Bankinter
FR	BNP Paribas, Crédit Agricole, Société Géneralé
DE	Deutsche Bank, Commerzbank, LBBW, BayernLB
BE	KBC
NL	ING-DiBa, Rabobank
DK	Danske Bank
SW	Skandinaviska Enskilda Banken, Svenska Handelsbanken, Swedbank
UK	HSBC, Barclays, Lloyds, Standard Chartered Bank
US	J.P. Morgan, Bank of America, Citigroup, Wells Fargo, Goldman Sachs, Morgan Stanley

The country codes are as follows: IT: Italy, ES: Spain, FR: France, DE: Germany, BE: Belgium, NL: Netherlands, DK: Denmark, SW: Sweden, UK: United Kingdom, US: United States of America.

Table 4.1: Description of banks in the sample

4.2.1 Specification of excess CDS premia

In line with Bekaert et al. (2005) and Bruyckere et al. (2013), the existence of sovereign-bank linkages is assessed by considering the co-movement between *excess* CDS premia, which is the co-movement between sovereign and bank credit risk above what can be explained by fundamental factors. Simply using CDS premia could be misleading, as periods of high market volatility usually enhance the co-movement. Therefore, the correlation between sovereign and bank CDS in country j at time t is decomposed as

$$\begin{aligned} E[\Delta CDS_{j,t}^{sov}\Delta CDS_{j,t}^{bank'}] = &\ E[(\beta_j^{sov}F_t^{'} + u_{j,t}^{sov})(\beta_j^{bank}F_t^{'} + u_{j,t}^{bank})^{'}] \\ = &\ \beta_j^{sov}E[F_t^{'}F_t]\beta_j^{bank'} + \underbrace{E[u_{j,t}^{sov}u_{j,t}^{bank'}]}_{Excess\ correlation}, \end{aligned} \tag{4.1}$$

where $\Delta CDS_{j,t}^{k}$ is the CDS premium change in percentage approximated by $ln(CDS_{j,t}^{k}) - ln(CDS_{j,t-1}^{k})$ to ensure time-series stationarity. Moreover, F_t defines a vector of common market factors, β_j^k captures the exposures to common market factors, and $u_{j,t}^{k}$ defines the residual premium for $k = \{sov, bank\}$. Hence, an increase in the co-movement can be driven by a higher correlation between the common factors, by a higher exposure of CDS premia to market factors, or by an increase in the residual correlation (Bruyckere et al., 2013). The latter is used as a measure of sovereign-bank dependence in this paper. To address the fundamental factors, the CDS data are regressed on three market factors.

First, the STOXX Europe 600 stock market index is utilized to control for the overall business climate in the European Union. The index represents 600 companies with large, mid, and small capitalization in 17 European countries. Second, the *VSTOXX* volatility index is considered to take the market-wide financial uncertainty into account. The index measures the implied volatility of options written on the STOXX Europe 50. Third, the iTraxx Europe is employed to control for overall credit risk. The index is a weighted average of the most liquid 5-year CDS in Europe and comprises 125 companies. Finally, a constant $\beta_{0,i,j}$ and autoregressive factors $\sum_p \phi_{i,j,p}\Delta CDS_{i,j,t-p}$ are included to account for serial correlation. The number of lags is chosen in line with the partial autocorrelation structure of each series. For the United States, the S&P500, the VIX volatility index, and the CDX CDS index are employed accordingly. Overall, the *excess* risk premium of a specific bank i in country j and the related sovereign in country j is captured by the residual component calculated as

$$\begin{aligned} u_{i,j,t} = \Delta CDS_{i,j,t} - \beta_{0,i,j} - \sum_p \phi_{i,j,p}\Delta CDS_{i,j,t-p} - \beta_{1,i,j} VSTOXX_t \\ -\beta_{2,i,j} STOXX_t - \beta_{3,i,j} iTraxx_t. \end{aligned} \tag{4.2}$$

To capture the overall banking industry in each country, banking sector indices are computed as a weighted average of individual bank excess premia

$$u_{j,t}^{bank} = \frac{\sum_i (\omega_{1,i,j} \times u_{i,j,t})}{\sum_i \omega_{1,i,j}}, \tag{4.3}$$

where the weight $\omega_{1,i,j}$ measures the sensitivity of a bank's default risk to government bond price changes obtained by regressing $\Delta CDS_{i,j,t} = \omega_{0,i,j} + \omega_{1,i,j}\Delta Bondprice_{j,t}$. Thus, banks that have a higher exposure to sovereign risk are assigned a higher weight. Finally, monthly averages are calculated from the daily indices. This eliminates daily noise to evaluate the fundamental sovereign-bank relation and also allows to assess the influence of policy uncertainty, which is unlikely to change day by day.[1] The latter is proxied by the monthly (European) economic policy uncertainty index of Baker et al. (2016). Using automated textual analysis, Baker et al. (2016) analyze the coverage of policy-related economic uncertainty in leading newspapers as an indicator for the intensity of concerns about policy uncertainty in the United States. Up till now, Baker's uncertainty index has been computed for several other countries and years back to 1985.

[1]Daily CDS are initially chosen to obtain reliable coefficient estimates in contrast to monthly data (3,048 versus 130 observations).

4.2.2 Continuous wavelet transform

Within the scope of this paper, continuous wavelet transformation (CWT) is applied, as it yields a subtler resolution than the discrete specification.

Univariate wavelet transform

Wavelet transformation decomposes a time series x_t into a set of different daughter functions, which are derived from a mother wavelet through scaling and translation in time. Therefore, the mother wavelet can be expressed as a function of the translation parameter τ and the scale parameter s. While the latter defines how the wavelet is stretched, the translation parameter determines the specific position of the wavelet (Tiwari et al., 2016). The general shape is given by

$$Wave_x(\tau, s) = \sum_t x_t \frac{1}{\sqrt{s}} \psi^\star \left(\frac{t-\tau}{s} \right), \tag{4.4}$$

where the normalization factor $1/\sqrt{s}$ ensures comparability across different time series and scales (Vacha and Barunik, 2012). Moreover, $\star$ denotes the complex conjugate and t indicates the time component. From a number of different mother wavelets, the Morlet function introduced by Grossmann and Morlet (1984) is utilized

$$\psi(t) = \pi^{-1/4} e^{i\omega t} e^{-t^2/2}. \tag{4.5}$$

The Morlet Wavelet is the most common specification in the field of economics and finance, as it secures the best trade-off between time and frequency localization (Ko and Lee, 2015; Singh et al., 2018; Vacha and Barunik, 2012; Wu and Wu, 2019; Stolbov et al., 2018). Moreover, the Morlet is a complex wavelet, wherefore the continuous wavelet transform can be divided into real and imaginary parts. The angular frequency parameter of Equation (4.5) is set to $\omega = 6$, which links the wavelet scale inversely to the frequency. This implies a Fourier factor of $2\pi/6$ for the conversion of scales to periods (Schmidbauer et al., 2017). The relation is used to convert the frequency into calendar months in order to ease the economic interpretations in this study.

Cross-wavelet transform

Following the univariate wavelet decomposition of two time series x_t and y_t, cross-wavelet analysis evaluates the similarity of $Wave_x(\tau, s)$ and $Wave_y(\tau, s)$ with respect to its periodic components and the development over time (Schmidbauer et al., 2017). The cross-wavelet transform is therefore given by

$$Wave_{xy}(\tau, s) = Wave_x(\tau, s)Wave_y^{\star}(\tau, s). \tag{4.6}$$

Based on the cross-wavelet transform, the complex wavelet coherency is defined as

$$\Gamma_{xy}(\tau, s) = \frac{S(Wave_{xy}(\tau, s))}{\sqrt{S(Wave_{xx}(\tau, s))S(Wave_{yy}(\tau, s))}}, \tag{4.7}$$

where S denotes a smoothing operator in time and scale. Finally, taking the absolute value of $\Gamma_{xy}(\tau, s)$ yields the (non-complex) wavelet coherency

$$R_{xy}(\tau, s) = \frac{|S(Wave_{xy}(\tau, s))|}{\sqrt{S(Wave_{xx}(\tau, s))S(Wave_{yy}(\tau, s))}}. \tag{4.8}$$

$R_{xy}(\tau, s)$ measures the local correlation between x_t and y_t in the time-frequency space with $0 \leq R_{xy}(\tau, s) \leq 1$ (Ko and Funashima, 2019). Values close to 1 show a high correlation, while values close to 0 depict a small dependence. In addition, the phase angle provides information about the direction of dependence i.e. positive or negative.

Following Aguiar-Conraria and Soares (2014), the *partial* wavelet coherency between x_t and y_t *after eliminating the influence of* z_t is defined as

$$R_{xy|z}(\tau, s) = \frac{|\Gamma_{xy} - \Gamma_{xz}\Gamma_{yz}^{\star}|}{\sqrt{(1 - R_{xz}^2)(1 - R_{yz}^2)}}. \tag{4.9}$$

Like the wavelet coherency, the partial wavelet coherency ranges from 0 to 1 and evaluates the direct relationship between x_t and y_t by controlling for other influences z_t. The resulting time-frequency relations are usually visualized with heat maps (Hkiri et al., 2016). To assess the statistical significance, the dependency patterns are tested against simulated white noise. Based on $n = 200$ simulations, p-values in the scale and time domains are derived. The null hypothesis of white noise states that there are no significant sovereign-bank dependencies over time and that there is no periodicity between sovereign and bank default risk (after controlling for the impact of EPU).

Cross-wavelet phase angle

Due to its complex feature, the cross-wavelet transform carries information about the synchronicity of two time series in terms of the local phase. The $Angle_{xy}(\tau, s)$ captures the phase difference of x_t over y_t at each scale and time computed as

$$\begin{aligned} Angle_{xy}(\tau, s) = Arg(Wave_{xy}(\tau, s)) &= Arg(Wave_x(\tau, s)) - Arg(Wave_y(\tau, s)) \\ &= Phase_x(\tau, s) - Phase_y(\tau, s), \end{aligned} \tag{4.10}$$

where $Phase_x(\tau, s)$ and $Phase_y(\tau, s)$ are angles in the interval $[-\pi; +\pi]$. Both measure the displacement of a periodic component relative to an origin in the time domain. An absolute value less (higher) than $\pi/2$ indicates that the two time series move in-phase (anti-phase), stating that both change in the same (different) direction (Stolbov et al., 2018; Schmidbauer et al., 2017). The lead-lag patterns are illustrated with arrows in cross-wavelet heat maps. Figure 4.2 depicts the interpretation of these arrows. The time series in Panel (b) and Panel (d) move in-phase, while the series in Panel (a) and Panel (c) move anti-phase.

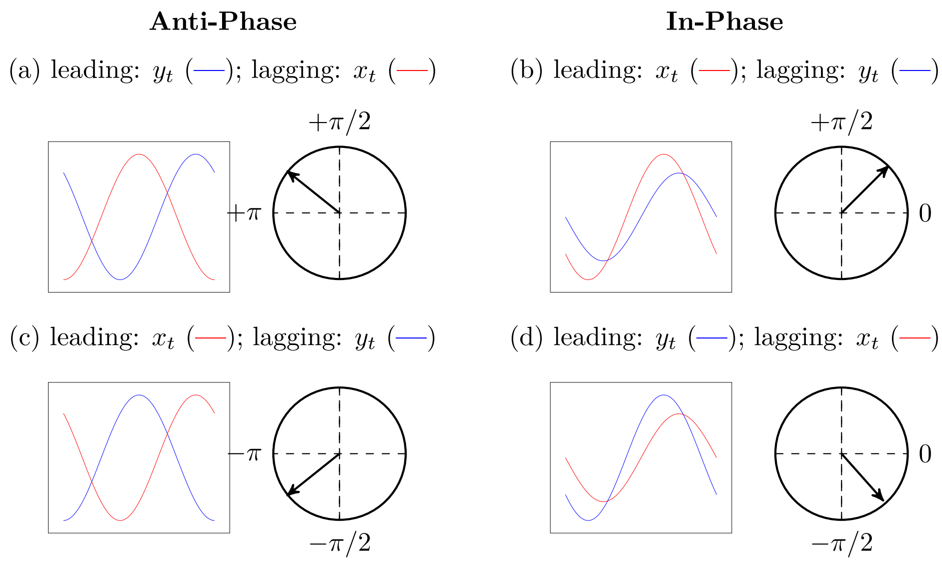


Figure 4.2: Illustration and interpretation of the phase difference

4.3 Results and discussion

The following section discusses the estimated wavelet coherency between sovereign and bank risk for all states. In addition, the relative importance of EPU is shown by eliminating the impact of policy uncertainty on the sovereign-bank coherency.

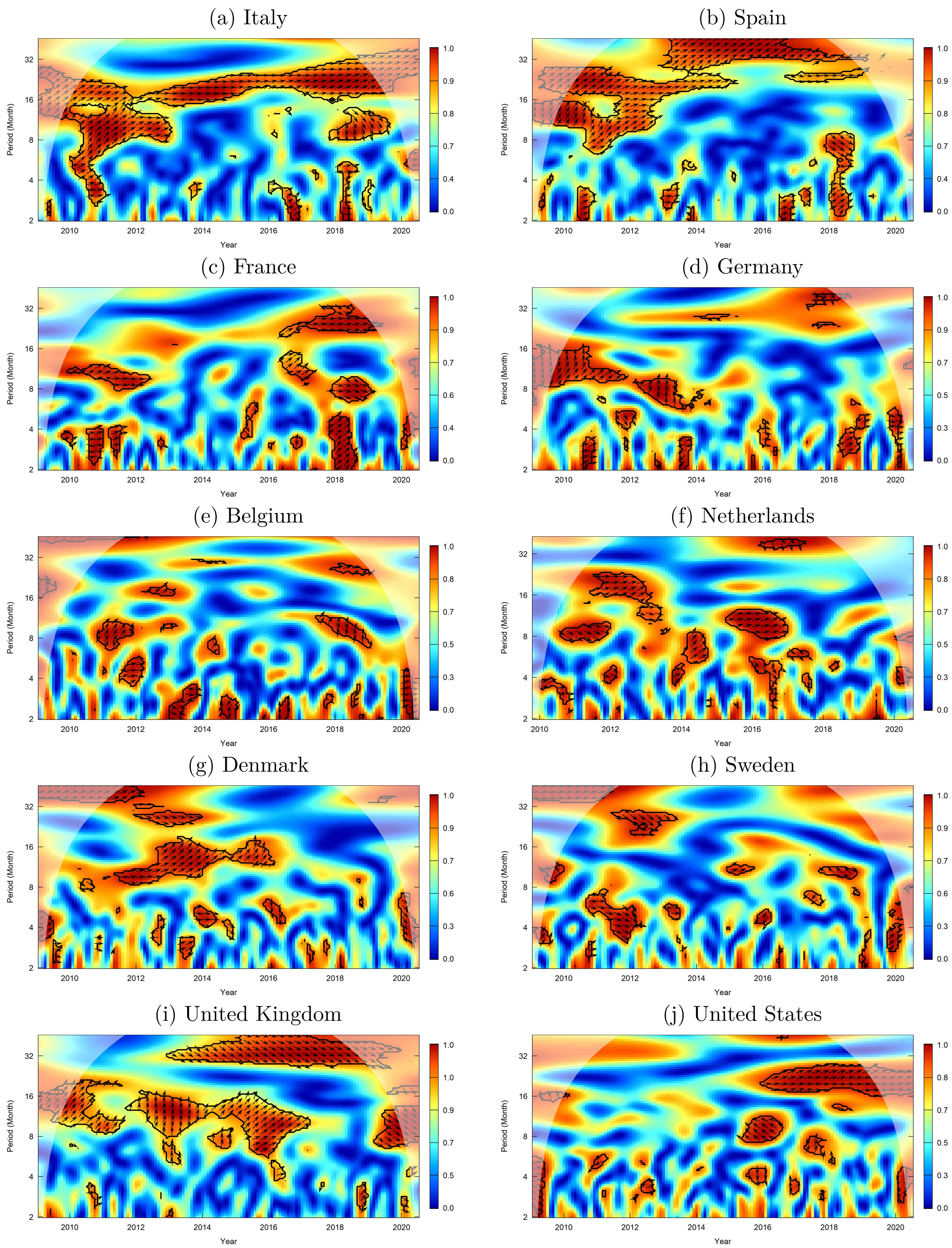
4.3.1 Sovereign-bank wavelet coherency

Figure 4.3 visualizes the wavelet coherency between sovereign and bank *excess* CDS premia, $u_{j,t}^{sov}$ and $u_{j,t}^{bank}$, for each country. The vertical axis corresponds to the wavelet scale expressed in months. The horizontal axis captures the time domain from 2009 to 2020. Red and orange colors indicate regions of high dependence between sovereign and bank excess premia, while blue and turquoise colors are associated with no or small dependence. The black contour lines depict the time-period domain of joint significance at a level of 5%. Arrows pointing to the right-up (left-down) signify that sovereign default risk leads banking sector default risk in case the time series move in-phase (anti-phase). Conversely, arrows pointing to the right-down (left-up) show that banking risk drives sovereign risk when the series move in-phase (anti-phase).

In general, sovereign and bank default risks almost always move in the same direction. For Italy, Spain, and France, significant and heavy default risk dependencies are present in early/mid-2018, where sovereign risk leads banking sector risk for periods of up to 6 months. In addition, some minor but equally directed dependencies are visible for Germany and Belgium. These findings are most likely triggered by the Italian parliament election in March 2018. Weeks of uncertain negotiations retrieved the fears of a European debt crisis caused by excessive spending intended by the new government.[2] The political stress not only raised domestic CDS premia but also affected countries, which held claims against the Italian government. In line with the dependency patterns, Spanish and French commercial banks are the main creditors of the Italian government apart from Italian banks.[3] For periods of 6–14 months, the relation reverses and banking risk leads sovereign risk. In total, this indicates the presence of a default risk loop at a specific point in time (i.e. the average across all frequencies). Considering the Brexit referendum as a second policy uncertainty event, sovereign risk leads U.K. banking sector risk for periods of up to 16 months. For longer horizons, the relation reverses. Again, this represents a policy-associated default risk nexus in the United Kingdom. In addition, some minor influences are visible in Italy, Spain, Germany, Belgium, and the Netherlands, where sovereign risk leads banking sector risk. In the United States, the nexus is less pronounced and moves out-of-phase. Moreover, there are only a few significant dependencies between 2014 and 2016, which may point to a successful implementation of the European Banking Union in 2014. The latest increases in dependency can be attributed to the COVID-19 pandemic.

[2] In June 2018, also the Spanish no-confidence vote against President Mariano Rajoy took place.

[3] In mid-2018, the holdings of Italian, Spanish, and French banks amounted to 353, 55, and 41 bn euros respectively (European Central Bank, 2018).



This figure shows the wavelet coherency between sovereign and bank risk. The vertical axis depicts the wavelet scale; the horizontal axis captures the time domain. Red and orange colors indicate high dependence; blue and turquoise colors show small dependence. The black lines depict areas of 5% significance. Arrows pointing right-up (right-down) show that sovereign (bank) risk leads banking (sovereign) risk.

Figure 4.3: Wavelet coherency between sovereign and bank default risk

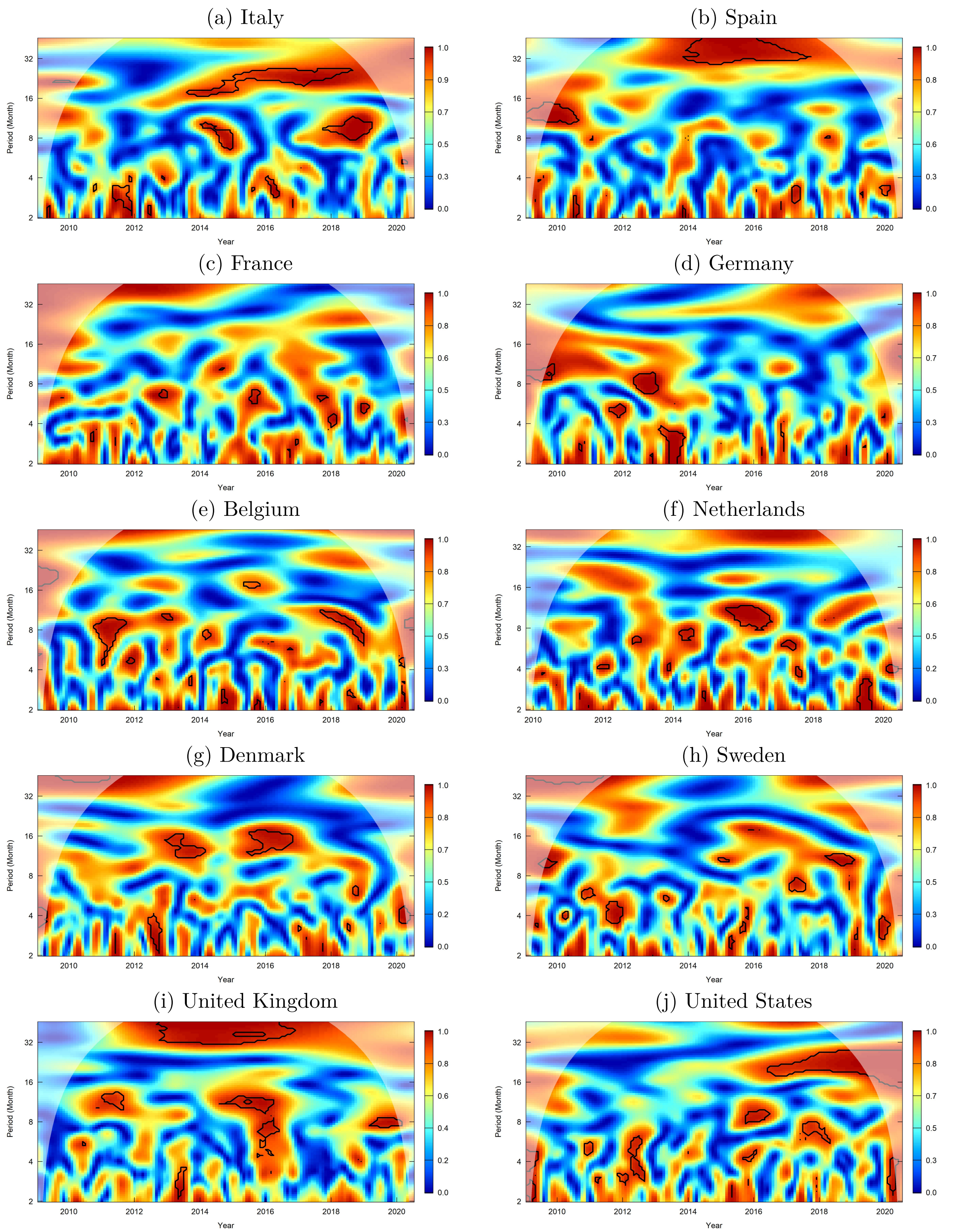
As a response to the economic downturn, a number of banks have increased their exposure to sovereign risk through large-scale purchases of sovereign debt securities. Finally, the results suggest that the sovereign-bank nexus is particularly pronounced for a horizon of up to 34 months.

4.3.2 Sovereign-bank partial wavelet coherency controlling for EPU

The patterns in Figure 4.3 have indicated that periods of high sovereign-bank dependence coincide with periods of high policy uncertainty. However, to conclude whether these linkages are actually associated with policy uncertainty, the partial wavelet coherency between sovereign and bank default risk is computed by controlling for EPU. The latter is proxied by the European policy uncertainty index of Baker et al. (2016) to take cross-country spillovers of policy uncertainty into account. For the United States, the U.S. EPU index is utilized. In line with the CDS data, percentage changes of EPU are computed as the first difference of the natural log. Figure 4.4 visualizes the resulting partial coherency. Again, the black contour lines depict the time-period domain of joint significance at a level of 5%.

Comparing the partial wavelet coherency in Figure 4.4 with the wavelet coherency in Figure 4.3, the sovereign-bank dependence is significantly lower once the influence of economic policy uncertainty is eliminated. In particular, most of the short-run relations disappear and only a few dependency patterns remain in mid-2016 and early/mid-2018 i.e. after the Brexit vote and the Italian parliament election. While most of the dependence in the euro area countries disappeared, some dependencies remain in the United Kingdom and the United States. This may suggest lower importance of EPU in these countries. Overall, the results demonstrate that uncertainty about (economic) policies is a significant driver of the dependence between sovereign and bank default risk. This is especially true for a horizon of up to 2 years.

Combining these results with existing research, the impact of policy uncertainty on economic activity can be illustrated with the use of a basic economy model, where households lend money to banks. Banks, in return, provide credits to firms, which use these loans to make investments. A shock in policy uncertainty is likely to reduce semi-durable expenditures of households and to increase precautionary savings (Aaberge et al., 2017). Firms may likewise decrease their investments, which enhances firm credit risk (Liu and Zhong, 2017). As this study demonstrates, higher economic policy uncertainty, moreover,



This figure shows the partial wavelet coherency between sovereign and bank risk by controlling for EPU. The vertical axis depicts the wavelet scale; the horizontal axis captures the time domain. Red and orange colors indicate high dependence; blue and turquoise colors show small dependence. The black lines depict areas of 5% significance.

Figure 4.4: Sovereign-bank partial wavelet coherency controlling for EPU

leads to greater sovereign and bank default risk. In order to prevent further losses, banks may additionally tighten their lending activity by rigorous monitoring of their borrowers, which slows down economic growth (Swamy, 2013; Bordo et al., 2016). The adverse effects are further amplified by the two-way feedback dependence between bank and sovereign default risk. Overall, economic policy uncertainty not only affects sovereign default risk, but also spills over to households, firms, and banks. This harms economic activity as it hampers economic growth, reduces stock prices (Hill et al., 2019), and increases the likelihood of defaults.

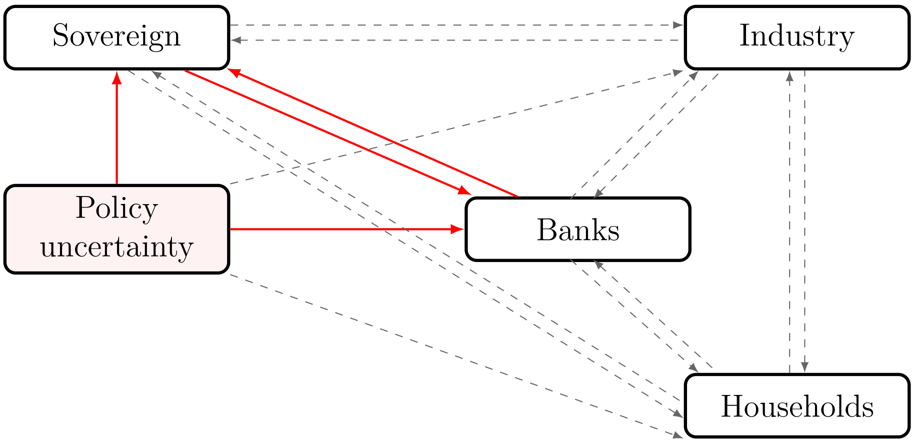


Figure 4.5: How policy uncertainty affects the economy

4.3.3 Robustness of the results

To assess the robustness of the results, a non-linear rather than linear regression model is estimated to obtain the excess CDS premia in Equation (4.2). The resulting cross-wavelet patterns are almost identical to the results of the linear mean model. Thus, there is no significant effect of a different mean specification. To evaluate the decomposition of CDS premia into a market and excess component, correlations between the excess indices and market factors are computed in Table 4.2. For both, bank and sovereign indices, the correlations with the fundamental market factors are almost zero. This points to the validity of Equation (4.1). Third, the individual CDS data are replaced by two market indices: An index of European sovereign default risk and an index of European banking sector default risk. In contrast to individual bank CDS, the banking sector index incorporates over 100 different time series and is less exposed to individual shocks. The wavelet coherency is depicted in Figure 4.6. The resulting coherency patterns support the prior results and show that the findings can be applied to the whole European Union. Finally, the methodological fit of the cross-wavelet transforms is evaluated by comparing the original time series with the reconstructed series originating from wavelet transformation. Figure 4.7 and Figure 4.8 in the Appendix show that the Morlet wavelet function properly decomposes the excess premia, such that the reconstructed and original series are almost identical.

	IT	ES	FR	DE	BE	NL	DK	SW	UK	US
Sovereign residuals $u_{j,t}^{sov}$										
VSTOXX	0.00	-0.00	0.00	0.00	-0.00	0.00	0.00	-0.00	0.00	0.00
iTraxx	0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.00	0.00	-0.00
STOXX	-0.00	0.00	-0.00	-0.00	0.00	-0.00	-0.00	0.00	-0.00	-0.00
Bank residuals $u_{j,t}^{bank}$										
VSTOXX	-0.00	-0.00	-0.00	0.00	-0.00	0.01	-0.00	-0.00	-0.00	-0.00
iTraxx	-0.00	-0.01	-0.00	-0.00	0.00	-0.00	-0.00	-0.00	-0.00	-0.01
STOXX	0.00	0.00	0.00	-0.00	0.00	-0.01	0.00	0.00	0.00	0.00

This table shows correlations of sovereign and bank residuals with the market factors. The correlations are based on residual log-returns of Equation (4.2) to assess the model fit. For the United States, *'VSTOXX'*, *'iTraxx'*, and *'STOXX'* are replaced by the *'VIX'*, *'CDX'*, and *'S&P500'*.

Table 4.2: Correlation of sovereign and bank residuals with market factors

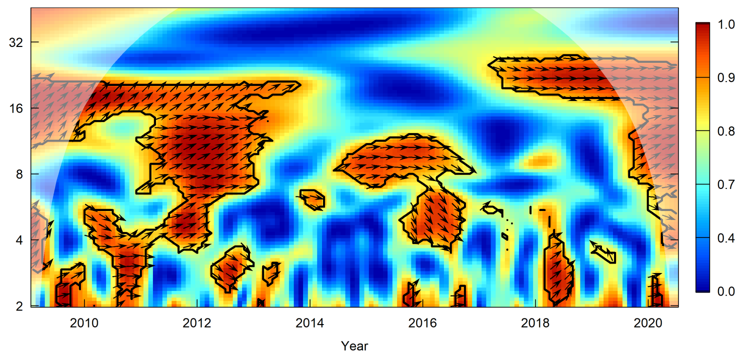


Figure 4.6: Wavelet coherency between European sovereign and banking CDS indices

4.4 Conclusion

This paper examines the co-movement between sovereign and bank default risk by introducing a time-frequency domain. Wavelet coherency analysis indicates that periods of great excess correlation coincide with periods of high policy uncertainty, such as observed in mid-2016 and early-2018. Controlling for the level of economic policy uncertainty, the sovereign-bank dependencies significantly weaken. This demonstrates a tightening of the sovereign-bank nexus in times of great economic policy uncertainty and uncertain election outcomes. Overall, the results highlight the relevance of political factors for the systemic risk in a country and underline the importance of joint European policies to mitigate sovereign-bank dependencies.

4.5 Appendix

j	Mean	Min	Max	SD	Skew	Kurt	Obs
IT	-0.00	-0.27	0.36	0.04	0.44	14.95	3,045
ES	0.00	-0.45	0.44	0.05	0.28	21.61	3,040
FR	-0.00	-0.25	0.76	0.05	1.87	29.27	3,048
DE	0.00	-0.51	0.60	0.06	-0.18	16.55	3,046
BE	-0.00	-0.33	0.48	0.05	0.37	15.14	3,047
NL	0.00	-0.59	0.46	0.07	-0.30	18.80	2,816
DK	-0.00	-0.35	0.32	0.06	0.12	9.90	3,045
SW	-0.00	-0.53	0.53	0.08	0.69	12.40	3,045
UK	0.00	-0.22	0.42	0.04	0.75	18.67	3,047
US	0.00	-0.27	0.33	0.03	0.15	18.62	3,047

This table reports descriptive statistics of sovereign residuals. *'Mean'* depicts the average residuals, where *'Min'* and *'Max'* indicate the lowest and highest residual premia. *'SD'*, *'Skew'*, and *'Kurt'* provide information about the standard deviation, skewness, and kurtosis of the distribution.

Table 4.3: Descriptive statistics of sovereign residuals

j	Mean	Min	Max	SD	Skew	Kurt	Obs
IT	0.00	-0.22	0.28	0.03	0.28	18.69	3,045
ES	0.00	-0.18	0.16	0.02	0.12	9.37	3,045
FR	0.00	-0.26	0.46	0.03	1.23	33.19	3,045
DE	0.00	-0.15	0.22	0.02	0.49	9.89	3,044
BE	-0.00	-0.47	0.25	0.03	-1.44	53.41	3,047
NL	0.00	-0.16	0.35	0.03	1.59	26.32	3,045
DK	-0.00	-0.34	0.38	0.03	0.97	38.18	3,046
SW	0.00	-0.50	0.41	0.05	0.00	19.52	3,045
UK	0.00	-0.27	0.35	0.02	0.89	32.73	3,045
US	-0.00	-0.21	0.20	0.02	0.25	13.51	3,043

This table reports descriptive statistics of bank residuals. *'Mean'* depicts the average residuals, where *'Min'* and *'Max'* indicate the lowest and highest residual premia. *'SD'*, *'Skew'*, and *'Kurt'* provide information about the standard deviation, skewness, and kurtosis of the distribution.

Table 4.4: Descriptive statistics of bank residuals

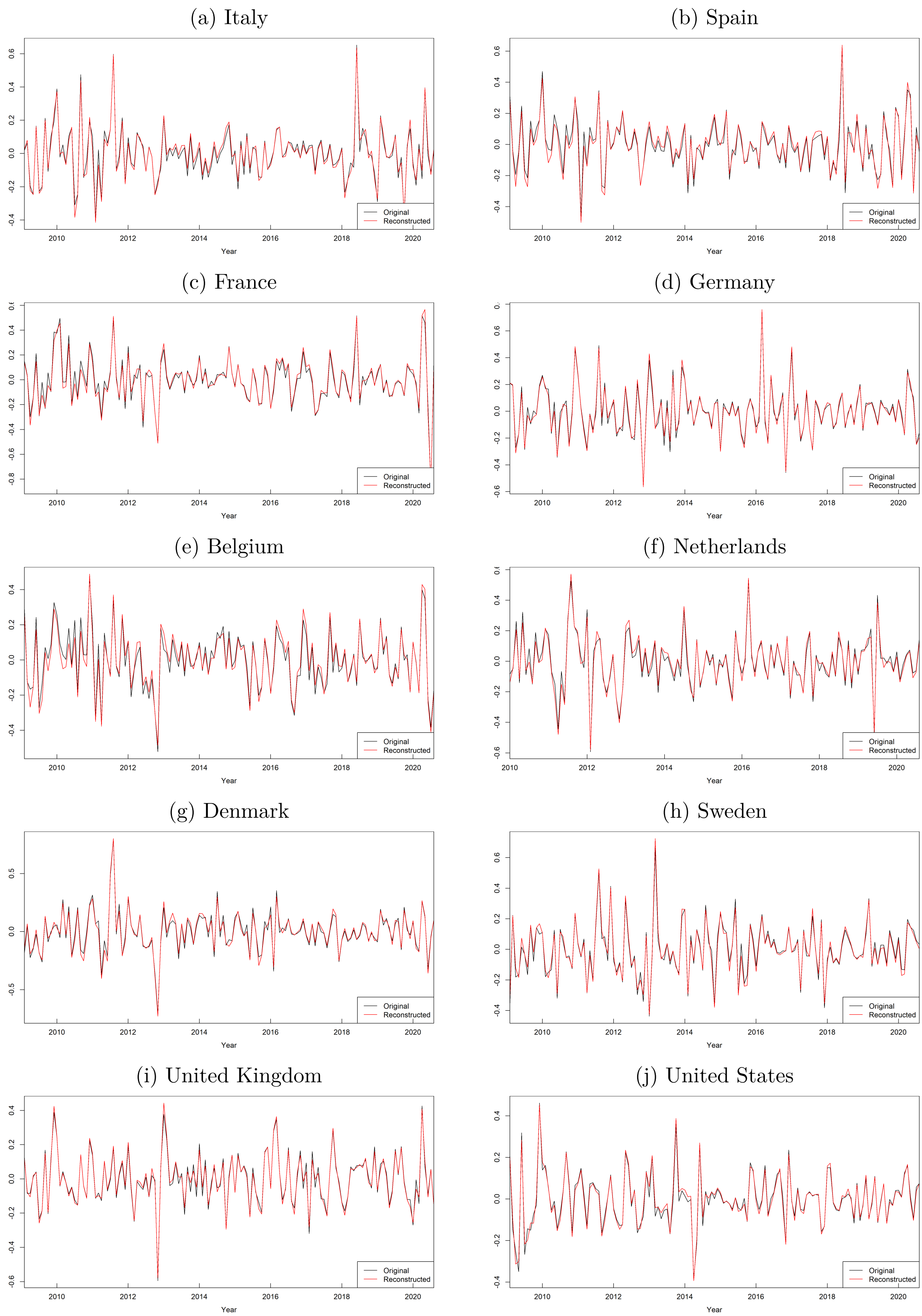


Figure 4.7: Original and reconstructed sovereign CDS after wavelet transformation

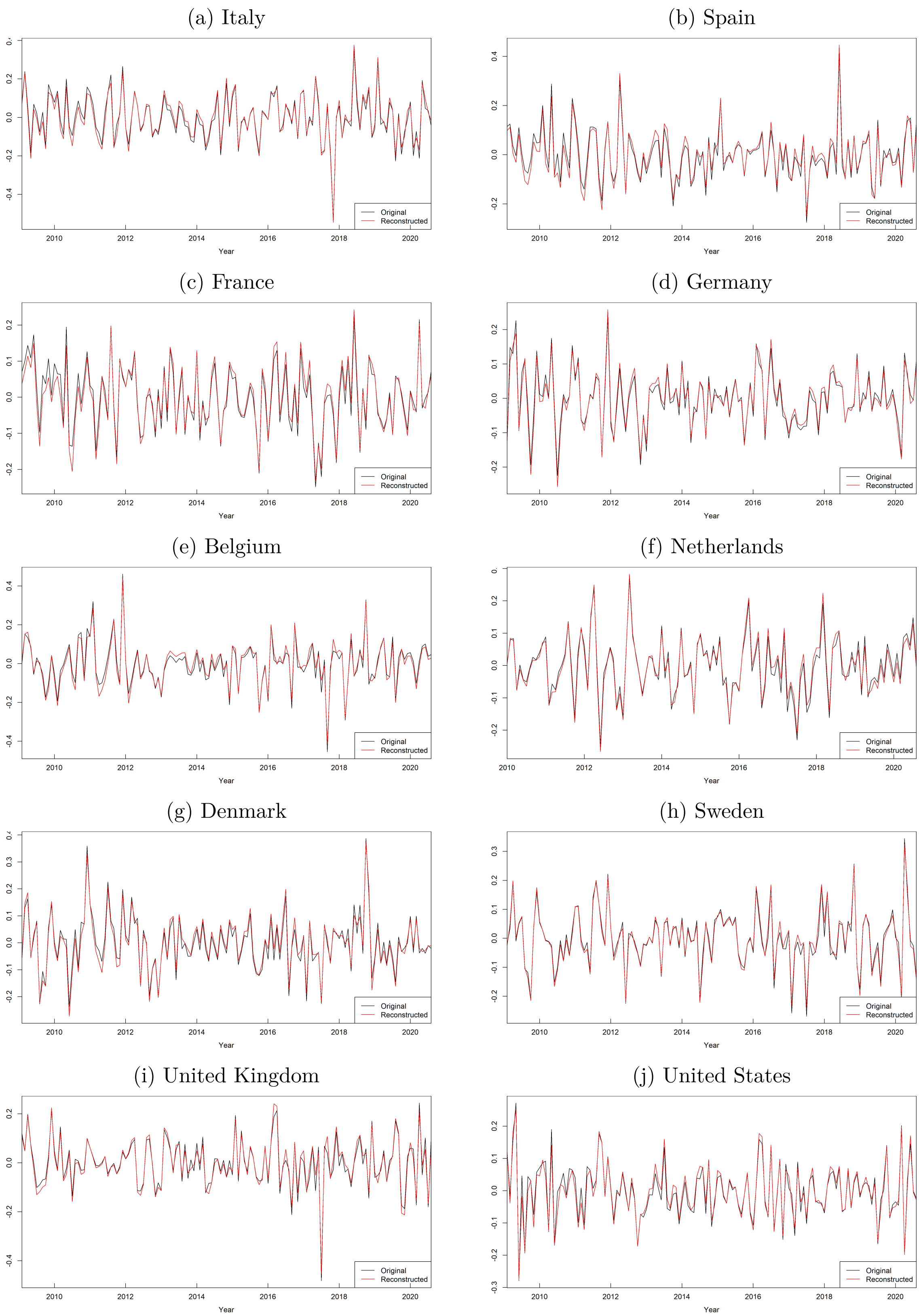


Figure 4.8: Original and reconstructed bank CDS after wavelet transformation

Chapter 5

Does the source of uncertainty matter? The impact of financial, newspaper and Twitter-based measures on U.S. banks

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Abstract

This study examines if the source of uncertainty (newspaper, Twitter, financial market) matters in its impact on bank stock returns in the United States. By applying discrete wavelet transformation, we model directional spillovers and Granger causality between uncertainty and bank returns for different time horizons. Our results demonstrate that this distinction between time horizons is crucial. Although newspaper and Twitter-based measures are correlated, they capture a different source of investor perception. Twitter-based uncertainty adversely affects bank stocks in the short run, while newspaper-based policy uncertainty is relevant in the medium run. Financial-based uncertainty, VIX, is the most important factor. Moreover, we find that the impact of uncertainty on bank returns is stronger during the COVID-19 pandemic and for banks with a high ratio of loans to total assets and large off-balance-sheet activities.

Keywords: Twitter uncertainty, policy uncertainty, VIX, bank returns, wavelets.

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5.1 Introduction and related literature

A large body of research is conducted to examine the impact of uncertainty on the behavior of households, businesses, and financial intermediaries. Assuming a basic model with a manufacturing and financial sector, households lend money to banks. Banks, in return, provide credits to producing firms, which use these loans to make investments (Bales and Burghof, 2022). Increasing uncertainty leads households to increase precautionary savings and reduce consumption (Aaberge et al., 2017). At the same time, firm investments and credit demand are expected to decrease. Diniz-Maganini et al. (2021) show that firms delay their investment decisions during periods of high uncertainty, while investors seek safe-haven assets to minimize risk and to wait for market recovery. This behavior lowers the overall demand and investment in an economy, which may ultimately harm firm cash flows, reduce profits, and adversely affect stock prices. Accordingly, Sarwar (2012) and Hitz et al. (2022) show a strong negative impact of implied volatility on stock market returns. Banerjee et al. (2007) investigate the relationship between future stock returns and current implied volatility, showing that VIX-related variables have strong predictive ability. Moreover, Arouri et al. (2016) reveal that an increase in policy uncertainty significantly reduces stock returns in the United States. This effect is found to be more persistent and pronounced during periods of extreme volatility. The study of Christou et al. (2017) extends these findings for a large sample of countries. Moreover, Pástor and Veronesi (2013) demonstrate that economic policy uncertainty (EPU) increases the risk premium of stocks, implying that financial uncertainty is an increasing function of EPU.

In the course of this study, we model the impact of uncertainty on U.S. bank stocks for different time horizons. Thereby, we address the research question if the source of uncertainty (newspaper, Twitter, financial market) matters in its impact on bank stock returns. We consider the banking sector, in specific, since banks are especially exposed to uncertainty shocks due to their role as financial intermediaries. Acharya et al. (2021) and Dunbar (2021) show a significant underperformance of bank stock returns relative to other firms during the COVID-19 uncertainty shock. They attribute this observation to high degrees of bank balance-sheet liquidity risk. However, a stable and healthy banking system is important for financial stability. Uncertainty shocks affecting the banking system can be transmitted to sovereigns via the sovereign-bank nexus. Bales and Burghof (2021) and Bales (2022*a*) demonstrate that higher levels of EPU increase the correlation between sovereign and bank default risk. Duan et al. (2021) show that pandemic-related uncertainty increases the systematic risk in the banking sector, where the adverse effects are more pronounced for large and highly leveraged banks. Bordo et al. (2016) and Berger et al. (2022), furthermore, demonstrate a significant negative impact of uncertainty on bank credit growth and liquidity creation. In times of high EPU, banks are not willing to finance additional debt, as they may expect rising non-performing loans and defaults, which hurt bank profitability (Ozili and Arun, 2023). Instead, banks tend to further tighten their lending activity by rigorous monitoring of their borrowers, which lowers bank profits additionally (Swamy, 2013). Besides uncertainty, the literature identifies several determinants of bank profitability, which is the most important indicator of bank (stock) performance. A large body of studies shows that bank profitability is affected by monetary policy (Altavilla et al., 2018), market structure (Mirzaei et al., 2013), bank credit supply (Ryoo, 2013), the low-interest rate environment (Bikker and Vervliet, 2017), productivity (Batten and Vo, 2019), and inflation (Tan and Floros, 2012), among others.

Since uncertainty is not directly observable, different measures are proposed in the literature. The CBOE Volatility Index (VIX) is widely used as a measure of financial uncertainty, capturing the 30-day ahead implied volatility of options written on the S&P500. High levels of the index usually coincide with high degrees of financial market turmoil. A second uncertainty measure was developed by Baker et al. (2016). Using automated textual analysis, the relative frequency of articles in ten leading U.S. newspapers containing the words *economy*, *policy*, and *uncertainty* is used as an indicator of policy uncertainty (EPU). Considering the rise of social media, Baker et al. (2021) created a Twitter-based economic uncertainty index (TEU). Like the EPU index, the TEU relates to the relative number of English tweets containing the words *economy* and *uncertainty*. However, the use of this measure provides some main advantages. While newspaper-based measures reflect individual opinions of experts or journalists, Twitter represents the beliefs of a large cross-section of social media users (Baker et al., 2021). Aharon et al. (2022) claim that Twitter has become a "new-era newspaper" that mediates between information providers and consumers. Nowadays, Twitter is used as an information source for retail investors, which is why tweets can have a large impact on the financial markets. Moreover, Twitter acts as a possible medium for the measurement of individuals' moods or sentiments. Figure 5.1 depicts the development of daily VIX, EPU, and TEU in the United States between 2012 and 2022. The series are standardized to ensure comparability across the measures. As Figure 5.1 indicates, the uncertainty indices closely co-move. Intuitively, a greater level of uncertainty affects the financial markets and attracts public attention through newspapers or tweets. Thus, the measures are expected to share some common drivers and influence each other. This study specifically explores the heterogeneity in these uncertainty measures and considers their impact on banking sector returns. To this end, we apply discrete wavelet methods, which allow us to derive conclusions for different time horizons. We demonstrate that the distinction between time horizons is crucial in the context of our research question and provides informational gains, emphasizing our contribution to the literature. One of the limitations in prior studies is the use of traditional econometric methods, which do not capture time and frequency information simultaneously (Gupta et al., 2018). Moreover, we consider the relation *between* the uncertainty measures utilizing PCA, unlike prior research. Understanding how newspaper, financial, and Twitter-based measures are related can provide valuable insights into how information is processed by the stock markets. In this context, Altig et al. (2020) highlight the need to distinguish between uncertainty measures, as they may capture different aspects of economic uncertainty. Subjective uncertainty measures like TEU or EPU may be important for firm-level risks in economic fluctuations, while the VIX relates to theories that link asset-pricing behavior.

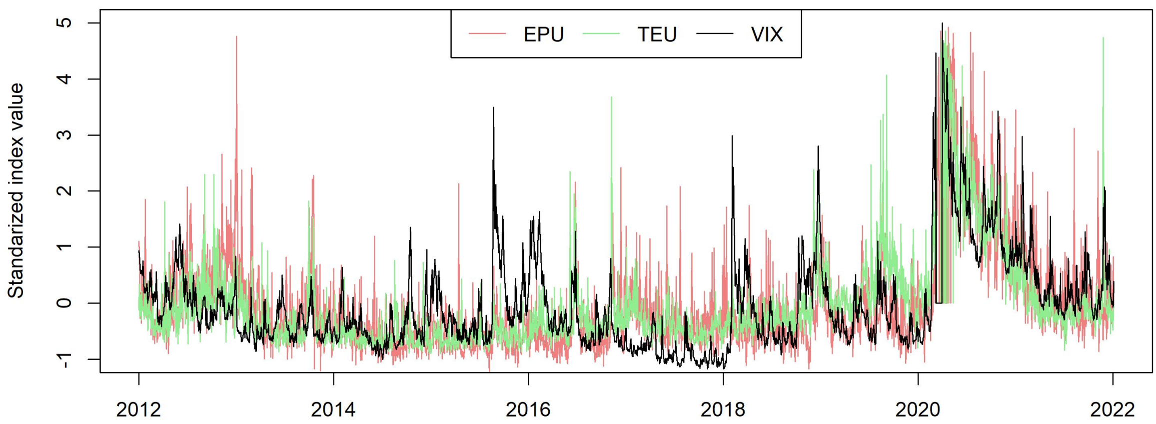

Figure 5.1: Development of daily VIX, EPU, and TEU in the United States

Our results demonstrate that the impact of uncertainty varies for different time horizons. We find that Twitter-based uncertainty negatively impacts bank stock returns in the short run, while policy uncertainty is important in the medium run. Moreover, we find two-way causality between TEU/VIX and returns in the short run. Financial market uncertainty is the most important factor for bank returns. Finally, we find that the impact of uncertainty on bank stocks is stronger during the COVID-19 pandemic and for banks with a high ratio of loans to total assets and large off-balance-sheet activities, measured by the ratio of derivatives to total assets. This knowledge is important for financial regulators and policymakers. If they have a better understanding of how uncertainty shocks are transmitted across different frequencies, they could react more effectively to stabilize the financial system. The remaining chapter is structured as follows: Section 5.2 introduces the data and methodological background, while Section 5.3 discusses the results. Finally, Section 5.4 reaches a conclusion.

5.2 Data and methodology

Table 5.1 depicts the overall sample of uncertainty measures and considered U.S. banks.

Abbr.	Bank	Total assets (2021)
Bank stock returns		
B1	J.P. Morgan Chase Bank	$3,025,285,000,000
B2	Bank of America	$2,258,832,000,000
B3	Wells Fargo Bank	$1,767,808,000,000
B4	Citibank	$1,661,507,000,000
B5	U.S. Bank National Association	$544,774,160,000
B6	Truist Bank	$498,944,000,000
B7	PNC Bank	$463,097,309,000
B8	TD Bank	$401,511,800,000
B9	The Bank of New York Mellon	$386,515,000,000
B10	Capital One	$363,521,558,000
B11	Charles Schwab Bank	$342,023,000,000
B12	State Street Bank and Trust Company	$311,181,000,000
B13	Goldman Sachs Bank	$271,652,000,000
B14	Fifth Third Bank	$203,174,120,000
B15	Morgan Stanley Bank	$175,627,000,000
B16	The Northern Trust Company	$169,571,085,000
B17	KeyBank National Association	$168,974,607,000
B18	Regions Bank	$146,476,000,000
B19	Manufacturers and Traders Trust Company	$142,219,684,000
B20	American Express National Bank	$132,754,617,000
B21	The Huntington National Bank	$122,837,617,000
B22	Silicon Valley Bank	$113,839,098,000
Uncertainty measures		
VIX	CBOE Volatility Index, implied volatility on the S&P500	
EPU	U.S. Newspaper-based economic policy uncertainty	
TEU	U.S. Twitter-based economic uncertainty	

The sample relates to the largest U.S. banks with total assets of at least $100,000,000,000. The asset values are obtained from the commercial bank ranking of the Federal Reserve Statistical Release on December 31, 2021.

Table 5.1: Description of the data sample

The sample follows three main selection criteria. First, we consider daily VIX, EPU, and TEU from January 1, 2012, to January 1, 2022, resulting in 2,613 observations. The time period is restricted by the availability of the TEU index, which starts in late 2011. Nevertheless, considering the number of users and tweets before 2012, the impact on the financial markets was low. Second, we focus on the U.S. market since the TEU and EPU indices are available on a daily rather than a monthly basis. This is important, as the media are expected to have an immediate and fast impact on the markets. Third, we select banks with total assets of at least $100 billion based on the commercial bank ranking of the Federal Reserve Statistical Release on December 31, 2021.[1] Thereby, we refer to the largest and most influential U.S. banks. For each bank, we obtain daily stock prices from Refinitiv Eikon. The news-based uncertainty measures are collected from Baker et al. (2016) and Baker et al. (2021). We use the unweighted U.S. TEU index, which weights all tweets equally and only considers tweets sent by users in the United States. By this, we do not put a higher weight on Twitter accounts with a large number of followers. Baker et al. (2021) mention that Barack Obama, Joe Biden, The New York Times, Kamala Harris, and Alexandria Ocasio-Cortez are among the top five followed accounts. However, we also employ the weighted TEU in the robustness check in Section 5.3.5, which takes the number of re-tweets and interactions into account. Thereby, we control for a possible bias caused by single influential tweets. Finally, we obtain the VIX from Refinitiv Eikon and exclude non-trading weekends from the sample.

5.2.1 Principal component analysis

In the first step, Principal Component Analysis (PCA) is applied to capture the *common source* of variation in U.S. bank returns and to eliminate bank-specific shocks (Bales and Burghof, 2021). Since uncertainty is considered a macroeconomic risk factor, which affects the whole banking system, we expect a significant impact on the first principal component of bank returns rather than the idiosyncratic part in stock returns (Nguyen et al., 2020). To avoid distorted results, standardization of all variables is applied (Nobre and Neves, 2019). Let $\boldsymbol{r} = (r_1, \ldots, r_p)$ denote a vector of p time series in log-difference calculated as $r_i = ln(p_{i,t}) - ln(p_{i,t-1})$ with related covariance matrix $\boldsymbol{\Omega_r}$. PCA reduces the dimension of the original data set by forming linear combinations of r_i to explain as much as possible of the variance in $\boldsymbol{\Omega_r}$. The principal component of order i is given by

$$y_i = a_{i1}r_1 + a_{i2}r_2 + \cdots + a_{ip}r_p, \tag{5.1}$$

[1]Federal Reserve Statistical Release (2021) - Large Commercial Bank Ranking.

where the weights $a_{i1}, \ldots, a_{ip}$ are chosen such that $\text{Var}(y_i)$ is maximized and $a_{i1}^2 + a_{i2}^2 + \cdots + a_{ip}^2 = 1$ applies. For further analysis, component loadings are estimated using the optimal weights (Tsay, 2010; Brooks, 2008). According to Kaiser (1961), the optimal number of components is given by the number of eigenvalues larger than one. An eigenvalue of $\lambda_i = 1$ states that the PC contains the same amount of information as the original data. Finally, the proportion of overall variance described by the principal of order i is given by

$$P_i = \frac{Var(y_i)}{\sum_{i=1}^{p} Var(r_i)} = \frac{\lambda_i}{\lambda_1 + \cdots + \lambda_p}. \tag{5.2}$$

5.2.2 Maximal overlap discrete wavelet transformation

Following Nobre and Neves (2019) and Bales (2022*b*), the commonality in bank stock returns, represented by predictions of the first principal component, and the uncertainty measures are decomposed into multi-horizon frequencies using wavelet transformation. In particular, a wavelet is a function that splits a signal into different components that reflect the evolution through time and at particular frequencies. Standard econometric methods, in contrast, only operate within the time domain (Singh et al., 2018). Wavelet transformation ordinates from the field of electrical engineering, where it is used to analyze local signals. Due to its main advantages, the method rapidly spread out and has been applied in several other areas, such as epidemiology, neuroscience, climatology, and oceanography. The application to the field of economics and finance is relatively recent, yet the range of implementation is potentially wide. The econophysics literature shows that wavelet tools yield robust estimates of non-stationary time series and are able to account for non-linearity in financial data (Hkiri et al., 2016). Therefore, we combine wavelets with conventional econometric methods to analyze data on a time and frequency domain. In the course of this study, we employ the Maximal Overlap Discrete Wavelet Transformation (MODWT) framework. The Maximal Overlap DWT has some advantages over the classical Discrete Wavelet Transform (DWT), as it overcomes adverse effects related to the choice of a starting point and does not require a dyadic length of the data, which avoids phase shifts (Feng et al., 2018; Yang, 2019). According to Ramsey (2002), any time series can be represented as a sequence of projections by father and mother wavelets, Φ and Ψ. While father wavelets describe the long-run components, mother wavelets define the deviations from the smooth components such that

$$\int \Phi(t)dt = 1 \quad and \quad \int \Psi(t)dt = 0. \tag{5.3}$$

In the MODWT framework, the scaling and translation coefficients are numerically derived from Daubechies' least asymmetric filter of length 8, LA(8). The LA(8) filter belongs to the group of orthogonal wavelets and provides outcomes that are less correlated across scales (Daubechies, 1988). Overall, the wavelet representation of a time series $x(t)$ is given by a linear combination of the wavelet functions

$$\begin{aligned} x(t) &= \sum_k S_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \cdots + \sum_k d_{j,k}\psi_{j,k}(t) + \cdots + \sum_k d_{1,k}\psi_{1,k}(t) \\ &= S_J(t) + D_J(t) + D_{J-1}(t) + \cdots + D_j(t) + \cdots + D_1(t). \end{aligned} \tag{5.4}$$

The highest-level approximation $S_J(t)$ is a smooth signal, while the detailed signals $D_1(t)$, $D_2(t)$, ..., $D_J(t)$ are related to oscillations of lengths 2, 4, ..., and 2^J (Gourène et al., 2019). In this study, $x(t)$ is decomposed into four components $D_1(t)$, $D_2(t)$, $D_3(t)$, and $D_4(t)$ to capture time horizons of 2–4, 4–8, 8–16, and 16–32 trading days respectively. This selection of J is based on the study of Bai et al. (2019), who show that most uncertainty spillovers are observable for time horizons of up to 2 months (40 trading days).

5.2.3 Specification of causality and volatility spillover

In line with Gourène et al. (2019), we estimate a bivariate time–frequency Vector AutoRegressive Model (VAR) to determine the causality between uncertainty and bank stock returns.[2] The VAR system for $j = \{1, 2, 3, 4\}$ is defined by

$$D_j(t) = \mu_j + \sum_{k=1}^{K} \Phi_{k,j} D_j(t-k) + \alpha_j EXOG_{t,j} + \epsilon_{t,j}, \tag{5.5}$$

where $D_j(t)$ is a bivariate vector of one of the uncertainty measures VIX, EPU, or TEU and the first principal of bank returns at scale j. Moreover, μ_j defines a vector of constants, $\epsilon_{t,j}$ is an independent distributed white noise process and $\Phi_{1,j}, \ldots, \Phi_{k,j}$ denote the autoregressive coefficient matrices. A lag length of $K = 4$ is chosen according to the information criterion of Akaike (1974). Finally, $EXOG_{t,j}$ relates to a set of control variables. In each specification, we include the remaining uncertainty measures as controls. For example, we estimate the causal impact of EPU on bank stock returns by holding constant the influence of TEU and VIX. In addition, we account for cross-country uncertainty spillovers by including U.K. EPU[3]. Likewise, we control for financial uncertainty that

[2] The hypothesis of non-linearity in the relationship between uncertainty and bank returns is rejected for all uncertainty measures and wavelet scales.

[3] U.K. policy uncertainty is the only EPU index that is available on a daily basis.

ordinates from Europe by including the implied stock market volatility index VSTOXX. After estimation, we assess Granger causality by calculating the Wald test statistic

$$WT = \left[e \times vec\left(\hat{\Phi}\right)\right]' \left[e\left(\hat{V} \otimes (D'D)^{-1}\right)e'\right]^{-1} \left[e \times vec\left(\hat{\Phi}\right)\right], \tag{5.6}$$

where D is a matrix of independent variables, $vec(\hat{\Phi})$ denotes the row vectorized coefficients of $\Phi = [\Phi_{1,j}, \ldots, \Phi_{k,j}]$, and $\hat{V} = T^{-1}\sum_{t=1}^{T} \hat{\epsilon_{t,j}}\hat{\epsilon_{t,j}}'$. Finally, e is a $[K \times 2(2K+1)]$ selection matrix under the null hypothesis of non-causality (Dungey et al., 2019). In addition to Granger causality, a decomposition of the forecast error variance (FEVD) can provide further insights into existing volatility spillovers between the variables in the VAR system. We follow the framework of Diebold and Yılmaz (2014) to establish directional spillovers. The method is based on the generalized variance decomposition of Koop et al. (1996) and has the advantage of not being dependent on the ordering of the variables. The contribution of variable s to the H-step-ahead forecast error variance of variable i is defined as

$$\theta_{is}^{g}(H) = \frac{\sigma_{ss}^{-1}\sum_{h=0}^{H-1}(e_i' A_h \sum e_s)^2}{\sum_{h=0}^{H-1}(e_i' A_h \sum A_h' e_i)}; \qquad H = 1, 2, \ldots, \tag{5.7}$$

where $\sum$ represents the covariance matrix for the error vector ϵ, σ_{ss} is the standard deviation of the error term for the sth equation, and e_i is the selection vector. Finally, A_h is a h-step moving average coefficient matrix. For the FEVD, we follow the suggestion of Diebold and Yılmaz (2014) and apply a 10-period-ahead forecast horizon. All entries of the variance decomposition matrix are normalized by the row sum

$$\tilde{\theta}_{is}^{g}(H) = \frac{\theta_{is}^{g}(H)}{\sum_{s=1}^{N}\theta_{is}^{g}(H)}, \tag{5.8}$$

such that the contributions to the forecast error variance sum up to one $\sum_{s=1}^{N}\tilde{\theta}_{is}^{g}(H) = 1$ and $\sum_{i,s=1}^{N}\tilde{\theta}_{is}^{g}(H) = N$ applies. The directional spillovers transmitted from variable s to all other variables in the system i, denoted as $S_{s\to i}^{g}$, and vice versa, $S_{i\to s}^{g}$, are calculated as

$$S_{s\to i}^{g} = \frac{\sum_{s=1, s\neq i}^{N}\tilde{\theta}_{is}^{g}(H)}{\sum_{i,s=1}^{N}\tilde{\theta}_{is}^{g}(H)} \times 100 = \frac{\sum_{s=1, s\neq i}^{N}\tilde{\theta}_{is}^{g}(H)}{N} \times 100 \tag{5.9}$$

$$S_{i\to s}^{g} = \frac{\sum_{s=1, s\neq i}^{N}\tilde{\theta}_{si}^{g}(H)}{\sum_{i,s=1}^{N}\tilde{\theta}_{si}^{g}(H)} \times 100 = \frac{\sum_{s=1, s\neq i}^{N}\tilde{\theta}_{si}^{g}(H)}{N} \times 100. \tag{5.10}$$

5.3 Results and discussion

This section presents and discusses the estimation results. First, we consider the underlying commonality in U.S. bank stock returns and the uncertainty measures. Figure 5.2 depicts the results of the Principal Component Analysis for both cases. The scree plots in Panel (a) and Panel (b) show the percentage of total variation explained by the component of order i. Moreover, the loadings plots in Panel (c) and Panel (d) depict the correlation between the original variables and the first two principal components.

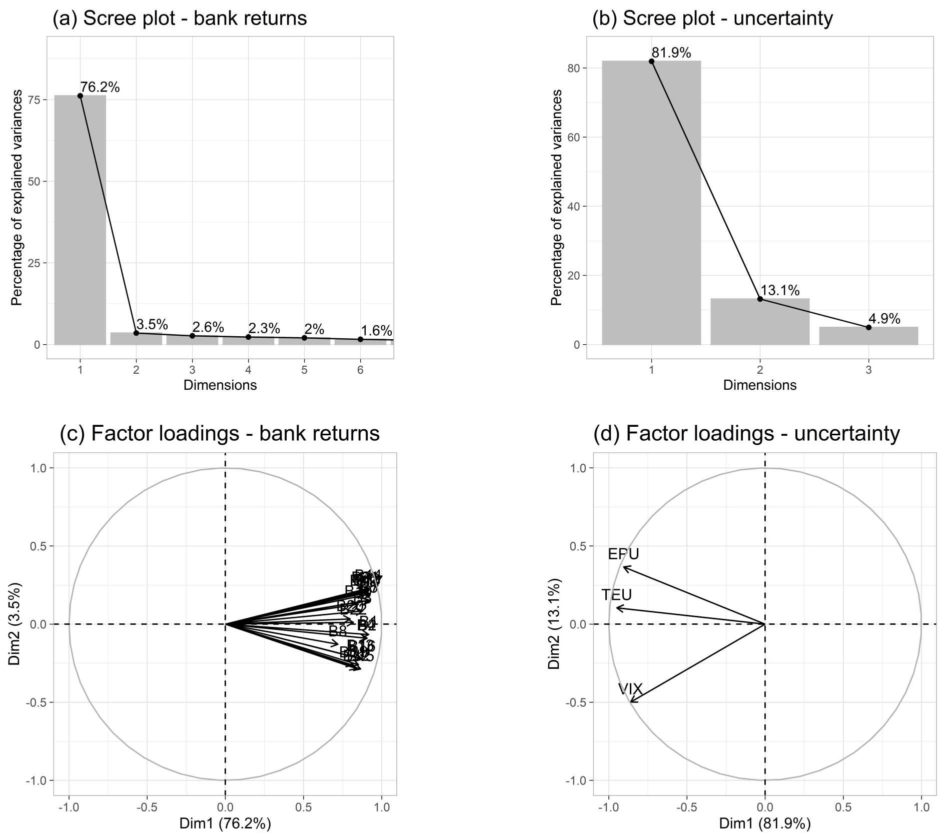

Figure 5.2: Principal component analysis of uncertainty and bank stock returns

Considering Panel (a) in Figure 5.2, 76.2% of the overall variation in U.S. bank returns can be attributed to just one component. This reveals a considerable amount of commonality, where the 22 banks almost equally contribute to the factor (Table 5.7 in the Appendix). The second principal captures about 3.5%. The loadings plot in Panel (c) reveals that all banks are positively correlated with the first principal, which can be interpreted as the general health of the economy. Thus, during economically good times, bank returns are likely to increase and vice versa. The exposure to component 2, in contrast, differs across banks. Likewise, the VIX, EPU, and TEU share a common variation of 81.9% in

Panel (b). The factor loadings reveal that all measures are negatively exposed to component 1 since uncertainty hampers economic growth. However, the measures considerably differ in the second dimension, which captures about 13.1% in Panel (d). While the VIX is negatively correlated with the second factor, EPU and TEU are positively exposed to this component. Considering the contributions to dimension 2 in Table 5.6 (Appendix), VIX accounts for over 60%, while the impact of TEU is almost zero. This highlights important differences between implied volatility and textual-based uncertainty measures like EPU and TEU. The different exposures can be explained by the fact that the VIX is little affected by investor perception changes or social media and usually captures macroeconomic fluctuations (Dutta et al., 2021). The EPU index, in contrast, is more responsive to political events. Taking the specific loading size into account, the TEU is located between EPU and VIX. This provides evidence that Twitter-based uncertainty captures financial uncertainty better than newspapers. Usually, newspapers contain a more founded and policy-related view of economic situations, while tweets contain a degree of subjectivity.

5.3.1 Assessing dynamic correlations

To further assess the relationship between EPU, TEU, and VIX, Figure 5.3 depicts dynamic correlations between the variables for different time horizons (scales). The estimates relate to a rolling window of 100 trading days. The individual decomposed time series are depicted in Figure 5.5 in the Appendix.

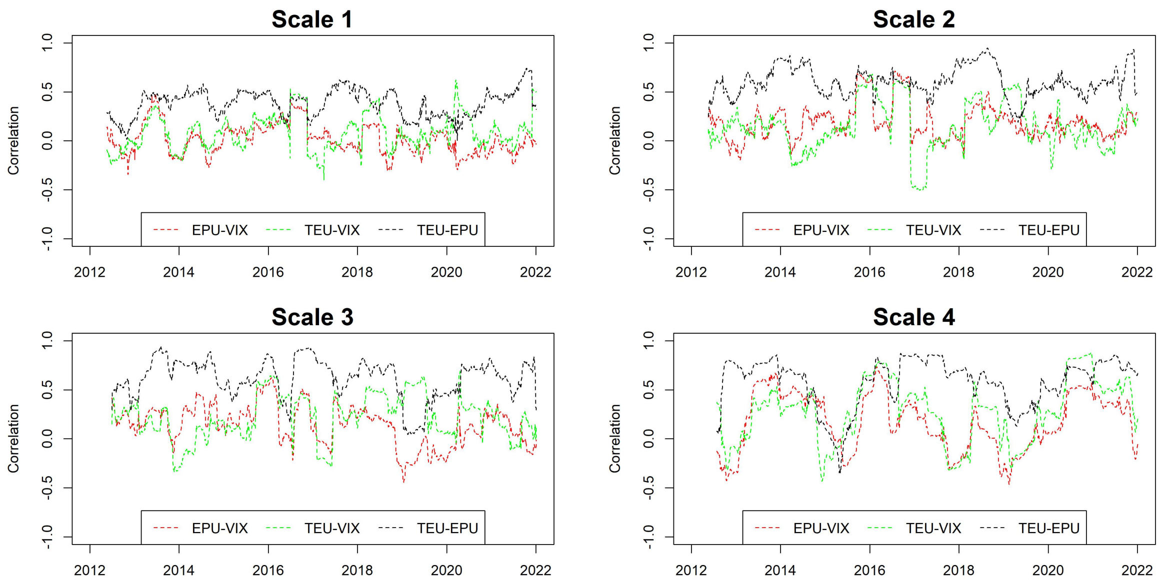

Figure 5.3: 100-day rolling correlation between VIX, EPU, and TEU

At first glance, the connection between EPU and TEU is the highest. The unconditional correlation shows that the dependence increases with j from 0.39 at scale 1 to about 0.60 for a horizon of 4–32 trading days (Table 5.2). This indicates that Twitter- and newspaper-based uncertainty substantially deviate in the very short run. One reason is that Twitter users are able to respond quickly to new circumstances, unlike newspapers. In line with this argument, Paulussen and Harder (2014) and Broersma and Graham (2013) show a steep rise in the number of tweets cited in newspapers and argue that social media has become a commonly used source for newspaper journalists. In addition, the correlation patterns between EPU–VIX and TEU–VIX are very similar, highlighting the thigh connection between EPU and TEU. Interestingly, the TEU–VIX correlation sharply dropped in the short run after the U.S. presidential election in November 2016. This illustrates that the financial markets and Twitter users had different perceptions about the election outcome. Finally, the unconditional correlation between VIX and EPU is the lowest with values between 0.03 and 0.19. Overall, the correlation structures are in line with the PCA results, showing that EPU and VIX differ the most.

	(a) Uncertainty measures			*(b) Uncertainty and bank returns*		
	EPU–VIX	TEU–VIX	TEU–EPU	VIX–PC1	EPU–PC1	TEU–PC1
D1	0.03	0.09	0.39	-0.59	-0.20	-0.34
D2	0.17	0.14	0.61	-0.52	-0.22	-0.23
D3	0.16	0.22	0.62	-0.20	-0.33	-0.16
D4	0.19	0.28	0.58	-0.08	-0.21	-0.20

Panel (a) shows correlations among the uncertainty measures. Panel (b) depicts correlations between the uncertainty measures and the common variation in bank returns (PC1). The correlations are computed for time horizons of D1: 2–4, D2: 4–8, D3: 8–16, and D4: 16–32 trading days.

Table 5.2: Correlation among uncertainty measures and bank returns by scale

Accordingly, Figure 5.4 depicts the multi-scale correlation between bank returns (first principal) and uncertainty over time. In strong consensus with the literature, the correlations are negative most of the time. Considering scale 1, financial uncertainty is more strongly correlated with bank stock returns (-0.59) than EPU (-0.20) or TEU (-0.34). However, the VIX–PC1 correlation is lower at scale 3 and scale 4. Overall, the results support the study of Houari (2022), which shows that shocks in the financial markets are relatively more important for the economy than changes in EPU. Likewise, Wang et al. (2020) demonstrate that implied volatility is more useful for predicting stock returns. Our study, moreover, provides evidence that Twitter uncertainty impacts bank stocks more heavily than EPU in the short run.

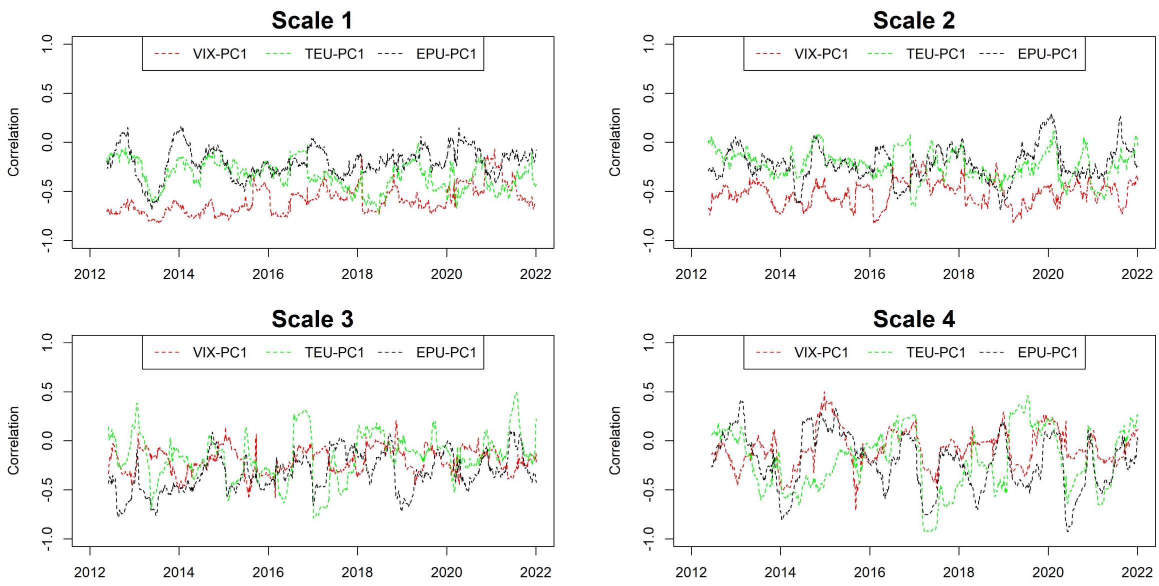

Figure 5.4: 100-day rolling correlation between PC1 and uncertainty

5.3.2 Assessing the direction of causality

The computation of dynamic correlations does not allow us to conclude the causal dependence structure between uncertainty and returns. For this reason, we conduct additional tests. Panel (a) in Table 5.3 reports the p-values of bivariate Granger causality tests, while Panel (b) states the size of volatility spillovers (in %) between uncertainty and the stock market. The net transmitters of volatility are indicated by a star.

		(a) Granger causality				*(b) Spillover*			
	Direction	D1 (2–4)	D2 (4–8)	D3 (8–16)	D4 (16–32)	D1 (2–4)	D2 (4–8)	D3 (8–16)	D4 (16–32)
(I)	VIX → PC1	0.00	0.01	0.01	0.02	11.54⋆	7.08	7.22⋆	6.10⋆
	PC1 → VIX	0.00	0.00	0.05	0.07	9.23	7.51⋆	3.15	0.17
(II)	EPU → PC1	0.19	0.08	0.02	0.01	0.19	1.28⋆	2.10⋆	2.25⋆
	PC1 → EPU	0.18	0.11	0.10	0.08	0.72⋆	1.01	0.14	0.30
(III)	TEU → PC1	0.01	0.04	0.08	0.20	6.22⋆	4.51⋆	4.25⋆	1.18
	PC1 → TEU	0.00	0.06	0.17	0.24	3.83	2.13	1.61	2.04⋆

This table shows causality between uncertainty and bank stock returns (PC1). Panel (a) depicts the p-value of bivariate Granger causality tests. Panel (b) depicts the size of volatility spillovers (in %) between uncertainty and bank stock returns, where a star indicates the net transmitter of volatility.

Table 5.3: Granger causality and directional spillovers by scale

Assuming a 5% significance level, the results in Table 5.3 show the existence of two-way dependence between financial market uncertainty and bank returns for a time horizon of 2–16 trading days (I). By definition, higher levels of the VIX are related to lower sentiment associated with the companies included in the S&P500. The growing uncertainty generates fear about market volatility, inducing noise feedback traders to sell off stocks. This leads to lower stock returns (Chen and Chiang, 2020). In line with the Granger causality results, large volatility spillovers between VIX and PC1 are observable in the short run. The assessment of net spillovers[4] indicates that the VIX is the main transmitter of volatility at scales 1, 3, and 4. This result is in line with prior literature, showing that financial uncertainty is the main predictor of stock volatility (Wang et al., 2020).

Considering (II), economic policy uncertainty does not Granger cause bank returns in the short run. However, there is a causal impact of EPU on PC1 at scales 3 and 4. This implies that the political environment and related uncertainty are important factors for banking sector profitability in the longer horizon. However, spikes or short-lasting shocks in policy uncertainty do not affect bank returns. Accordingly, EPU is a net transmitter of volatility to the stock market for a horizon of 4–32 trading days. Unlike EPU, Twitter-based uncertainty impacts the markets in the short run and acts as a net transmitter of volatility at scales 1–3 (III). This, again, emphasizes the different impacts of EPU and TEU and provides evidence for an inter-temporal dependence between both measures. If investors pay more attention to social media news, information gets more quickly integrated into the asset prices (Bashir and Kumar, 2022). Accordingly, the study of Aharon et al. (2022) argues that Twitter-based uncertainty can better capture consumers' uncertainty in the short term. This fact likely explains the different effects of both measures in the short period. In return, bank stock returns also impact the TEU in the short run. This, moreover, reveals that tweets affect the stock markets, causing more people to tweet about the developments, which, in return, affects the markets again. Considering the size of volatility spillovers, TEU affects bank stocks relatively more than EPU. This underlines the importance and power of social media. Finally, Table 5.3 indicates that the VIX is the most influential factor for bank stock returns in our sample, which extends the study of Elsayed et al. (2022) about time-frequency implications for the banking sector. Overall, the consideration of causality provides important findings that although TEU and EPU are highly correlated, both measures capture a different source of investor perception in the short run.

[4]For example, the VIX–PC1 net spillovers at scale 1 are calculated as 11.54–9.23 = 2.31.

5.3.3 Do bank asset allocations alter the impact of uncertainty on bank returns?

In the previous analysis, we computed the first principal component of the *overall sample* to extract the common variation in bank returns. However, the impact of uncertainty may differ across banks with different asset allocations. Existing literature reveals that the composition of the balance sheet, like the ratio of debt to equity or the proportion of total loans, shapes the risk structure of banks and may affect stock prices (Haq and Heaney, 2012). Among other factors, Saunders and Cornett (2014) identify four main sources of bank risk: Credit risk, interest rate risk, liquidity risk, and market risk. Credit risk is possibly the most important risk in banking when it comes to potential loss. Credit risk relates to the possibility that loans may not be paid, causing serious financial problems. Interest rate risk is linked to the exposure of banks' profits to changes in the interest rate, while liquidity risk is associated with the likelihood that customer demand for funds may require the sale of bank assets. Finally, market risk is related to a bank's exposure to extreme changes in market conditions, such as the COVID-19 pandemic. We specifically address the pandemic impact in Section 5.3.4. In addition, the risks associated with bank off-balance-sheet activities have become of increasing importance during the last years. Off-balance-sheet items are contingent assets or liabilities that may expose institutions to credit risk, liquidity risk, or counterparty risk, which are not reflected in the balance sheet. To account for different asset allocations, we obtain financial and regulatory reporting data for each bank from the Federal Deposit Insurance Corporation (FDIC). In particular, we consider four balance sheet measures, which may alter the impact of uncertainty on bank returns. In Table 5.4, we consider the proportion of total bank equity as a first factor. Usually, a higher ratio of bank equity is associated with lower default and liquidity risk. For that reason, many large banks must meet some minimum equity capital requirements. Second, we relate to the ratio of bank loans to overall bank assets to capture credit risk conditions. Apart from the quality of loans, we assume that a higher fraction of (risky) loans, ceteris paribus, increases the risk of loan defaults. Third, we account for a bank's government exposure by considering the ratio of U.S. government securities to total bank assets. Finally, we measure off-balance-sheet risk by the ratio of derivatives to total bank assets. Based on the median value of each measure, we divide the overall sample of banks into two groups of high (H) and low (L). Table 5.4 depicts the balance sheet measures along with the assigned group. Following our methodological approach in Section 5.2, we conduct PCA for each group and measure. Afterward, we assess the impact of uncertainty on bank returns via Granger causality and volatility spillover.

Bank	Equity (%)		Loans (%)		Gov. assets (%)		Derivatives (%)	
B1	10.53	L	40.63	L	12.24	L	2,027.08	H
B2	11.45	H	52.31	L	22.12	H	921.92	H
B3	9.77	L	54.55	H	18.19	H	703.94	H
B4	10.37	L	45.11	L	12.66	L	2,841.88	H
B5	10.16	L	61.25	H	23.41	L	118.85	H
B6	13.92	H	65.55	H	15.96	L	64.01	L
B7	10.51	L	59.89	H	17.91	L	112.91	H
B8	12.54	H	47.28	L	18.51	H	73.36	L
B9	8.35	L	8.04	L	27.59	H	382.70	H
B10	13.09	H	48.30	L	18.94	H	57.06	L
B11	6.85	L	8.46	L	64.82	H	0.14	L
B12	10.51	L	10.89	L	23.82	L	1,007.81	H
B13	12.83	H	36.53	L	3.21	H	18,583.46	H
B14	13.73	H	65.37	H	17.80	L	73.83	L
B15	9.59	L	76.68	H	14.15	H	0.84	L
B16	6.88	L	23.04	L	37.46	H	229.86	H
B17	11.83	H	66.91	H	22.23	H	84.28	L
B18	13.07	H	65.85	H	17.36	L	116.55	H
B19	12.66	H	75.14	H	7.32	L	91.22	L
B20	11.22	H	79.66	H	4.23	L	0	L
B21	11.80	H	69.37	L	17.95	L	61.10	L
B22	7.20	L	46.96	H	37.11	H	24.12	L
Mean	10.86		50.35		20.68		1,253.50	
Median	10.88		53.43		18.07		102.07	

Financial & Regulatory Reporting data are obtained from the Federal Deposit Insurance Corporation (FDIC), considering pre-COVID-19 levels of 2019-Q4. *'Equity'* indicates the percentage of total bank equity. *'Loans'* depicts the ratio of loans to overall bank assets. *'Gov. assets'* states the ratio of U.S. government securities to total bank assets. *'Derivatives'* indicates the ratio of derivatives to total assets. *'L/H'* = {Low, High} defines the group based on the median value of the respective measure.

Table 5.4: Formation of bank groups

Table 5.5 and Table 5.6 depict the resulting Granger causality and volatility spillover for each group and measure. Considering Table 5.5, the time-frequency impact of uncertainty does not considerably differ between banks with a low or high ratio of equity capital. In specific, the Granger causality p-values yield almost the same qualitative results as Table 5.3. That is, Twitter-based uncertainty Granger causes bank stocks in the very short run, while EPU Granger causes returns in the medium run. Again, VIX is the most important factor, which affects the returns across all time horizons. These findings are in line with the size of volatility spillovers, which differ only marginally between both groups.

Thus, banks with a low and high proportion of equity capital are exposed to uncertainty to the same extent in our sample. In contrast, we find that banks with a higher ratio of loans to total assets are more affected by all three uncertainty measures. Specifically, the results show that low loan/assets banks are affected by EPU in the medium run in line with prior results, while EPU also Granger causes stock returns of high loan ratio banks in the short run. In addition, the impact of uncertainty significantly differs between both groups in terms of volatility spillover. For the VIX and TEU, the short-term spillovers differ between 6.87% vs. 15.81% and 4.87% vs. 12.28%. Economically, banks with a higher loan ratio, ceteris paribus, face a higher level of credit risk, which ultimately alters the elasticity of bank stocks to uncertainty shocks. These results support the study of He and Niu (2017), who find that the impact of uncertainty is more pronounced for banks with a high ratio of loans to assets. Accordingly, a recent study of Dang and Nguyen (2021) demonstrates that banks' balance sheet reactions to uncertainty are more pronounced for banks with high loan credit risk.

Considering Table 5.6, we do not find evidence that the amount of U.S. sovereign securities held by banks affects their exposure to uncertainty. For both groups, the Granger causality results and volatility spillover are relatively similar and do not differ from the results in Table 5.3. The sovereign-bank nexus literature suggests that banks are linked to the financial health of their governments (Acharya et al., 2014). However, U.S. government securities are perceived to be almost risk-free and holding these securities does not reduce other sources of risk, like credit or liquidity risk. Finally, the results indicate that banks with a high engagement in off-balance-sheet activities, measured by the fraction of derivatives, are more exposed to uncertainty shocks. While the Granger causality results do not differ in their main conclusions, the volatility spillovers from uncertainty to bank returns are significantly larger for banks with a high ratio of derivatives to total assets. Hence, large U.S. banks are more affected by financial market and Twitter-based uncertainty if they hold a higher fraction of derivatives. These results are in line with a series of controversial studies. Although credit derivatives are important for securitizing and hedging credit risk, Instefjord (2005) reveals that derivatives may also destabilize the banking sector. Accordingly, Huan and Parbonetti (2019) consider a sample of 555 banks in 18 developed countries, demonstrating that banks' use of financial derivatives increases their risk. Li and Marinč (2014) specifically show that the use of interest, exchange rate, and credit derivatives corresponds to a greater level of interest and credit risk. Finally, Papanikolaou and Wolff (2014) argue that large off-balance-sheet actives, in general, make banks more vulnerable to financial shocks.

	Direction	(a) *Granger causality* D1 (2–4)	D2 (4–8)	D3 (8–16)	D4 (16–32)	(b) *Spillover* D1 (2–4)	D2 (4–8)	D3 (8–16)	D4 (16–32)
Low proportion of bank equity									
(I)	VIX → PC1	0.00	0.02	0.02	0.01	10.81⋆	6.68	7.01⋆	7.07⋆
	PC1 → VIX	0.00	0.01	0.05	0.07	8.66	7.19⋆	3.11	0.16
(II)	EPU → PC1	0.18	0.12	0.03	0.03	0.19	1.49⋆	2.22⋆	2.23⋆
	PC1 → EPU	0.19	0.09	0.10	0.09	0.84⋆	0.97	0.41	0.31
(III)	TEU → PC1	0.01	0.02	0.08	0.25	7.05⋆	4.54⋆	4.37⋆	0.98
	PC1 → TEU	0.01	0.07	0.16	0.24	3.89	2.18	1.64	2.09⋆
High proportion of bank equity									
(I)	VIX → PC1	0.00	0.01	0.01	0.02	11.08⋆	7.08	7.07⋆	6.47⋆
	PC1 → VIX	0.00	0.00	0.05	0.07	9.20	7.51⋆	3.15	0.17
(II)	EPU → PC1	0.19	0.08	0.02	0.01	0.22	1.28⋆	2.10⋆	2.25⋆
	PC1 → EPU	0.14	0.11	0.10	0.08	0.72⋆	0.98	0.01	0.30
(III)	TEU → PC1	0.03	0.02	0.08	0.20	7.22⋆	4.58⋆	4.25⋆	1.11
	PC1 → TEU	0.01	0.08	0.17	0.24	3.81	2.18	1.61	2.04⋆
Low ratio of bank loans to total assets									
(I)	VIX → PC1	0.03	0.05	0.09	0.12	6.87⋆	5.00	5.02⋆	4.41⋆
	PC1 → VIX	0.02	0.07	0.08	0.07	4.23	5.19⋆	3.58	0.43
(II)	EPU → PC1	0.39	0.08	0.05	0.08	0.14	1.11	2.11⋆	2.18⋆
	PC1 → EPU	0.14	0.21	0.22	0.11	0.72⋆	1.11	0.01	0.15
(III)	TEU → PC1	0.04	0.08	0.19	0.20	4.87⋆	3.00⋆	3.06⋆	1.39
	PC1 → TEU	0.05	0.08	0.19	0.24	2.98	2.08	1.43	1.54⋆
High ratio of bank loans to total assets									
(I)	VIX → PC1	0.00	0.00	0.00	0.04	15.81⋆	12.83⋆	11.30⋆	9.41⋆
	PC1 → VIX	0.00	0.00	0.01	0.09	10.24	8.19	6.55	2.74
(II)	EPU → PC1	0.05	0.04	0.02	0.08	3.74⋆	4.81⋆	4.01⋆	4.98⋆
	PC1 → EPU	0.19	0.11	0.18	0.21	1.45	1.28	0.08	0.59
(III)	TEU → PC1	0.01	0.02	0.11	0.25	12.28⋆	11.18⋆	7.12⋆	4.66⋆
	PC1 → TEU	0.00	0.00	0.18	0.14	6.31	4.98	3.42	2.18

This table shows causality between uncertainty and bank stock returns (PC1) by asset allocation measure. Panel (a) depicts the p-value of bivariate Granger causality tests. Panel (b) depicts the size of volatility spillovers (in %) between uncertainty and bank stock returns, where a star indicates the net transmitter of volatility.

Table 5.5: Granger causality and directional spillovers by scale and asset allocation I

	Direction	(a) Granger causality D1 (2–4)	D2 (4–8)	D3 (8–16)	D4 (16–32)	(b) Spillover D1 (2–4)	D2 (4–8)	D3 (8–16)	D4 (16–32)
Low ratio of government securities to total assets									
(I)	VIX → PC1	0.01	0.02	0.01	0.02	11.51⋆	7.14	7.05⋆	5.98⋆
	PC1 → VIX	0.01	0.01	0.08	0.06	9.31	7.22⋆	3.19	0.21
(II)	EPU → PC1	0.18	0.08	0.03	0.01	0.22	1.21⋆	2.10⋆	2.22⋆
	PC1 → EPU	0.13	0.11	0.12	0.08	0.73⋆	1.23	0.01	0.34
(III)	TEU → PC1	0.02	0.02	0.08	0.38	6.87⋆	5.01⋆	4.38⋆	1.13
	PC1 → TEU	0.01	0.08	0.16	0.22	3.68	2.10	1.61	2.17⋆
High ratio of government securities to total assets									
(I)	VIX → PC1	0.01	0.01	0.02	0.02	11.53⋆	6.58	7.14⋆	6.22⋆
	PC1 → VIX	0.01	0.02	0.08	0.6	9.29	7.33⋆	3.18	0.10
(II)	EPU → PC1	0.19	0.08	0.03	0.02	0.19	1.28⋆	2.11⋆	2.30⋆
	PC1 → EPU	0.14	0.11	0.11	0.08	0.70⋆	1.08	0.04	0.28
(III)	TEU → PC1	0.03	0.02	0.08	0.17	6.72⋆	4.87⋆	4.35⋆	1.11
	PC1 → TEU	0.02	0.07	0.17	0.23	3.70	2.09	1.58	2.14⋆
Low ratio of derivatives to total assets									
(I)	VIX → PC1	0.04	0.05	0.05	0.09	7.82⋆	6.01	5.14⋆	5.10⋆
	PC1 → VIX	0.04	0.05	0.09	0.12	6.01	6.04⋆	3.55	0.23
(II)	EPU → PC1	0.25	0.16	0.06	0.05	0.19	1.05⋆	2.48⋆	2.26⋆
	PC1 → EPU	0.15	0.10	0.10	0.09	0.71⋆	0.67	0.05	0.18
(III)	TEU → PC1	0.04	0.02	0.14	0.36	5.82⋆	4.55⋆	3.95⋆	1.09
	PC1 → TEU	0.04	0.15	0.17	0.23	3.77	2.74	1.69	2.03⋆
High ratio of derivatives to total assets									
(I)	VIX → PC1	0.00	0.00	0.00	0.02	14.12⋆	14.87⋆	11.01⋆	7.12⋆
	PC1 → VIX	0.00	0.00	0.03	0.08	11.93	9.46	3.15	0.17
(II)	EPU → PC1	0.15	0.11	0.01	0.01	0.05	2.87⋆	3.95⋆	3.74⋆
	PC1 → EPU	0.14	0.11	0.11	0.09	1.69⋆	1.36	0.98	0.68
(III)	TEU → PC1	0.03	0.02	0.07	0.20	8.94⋆	7.97⋆	3.33⋆	1.01
	PC1 → TEU	0.00	0.11	0.14	0.20	4.36	3.98	1.51	2.09⋆

This table shows causality between uncertainty and bank stock returns (PC1) by asset allocation measure. Panel (a) depicts the p-value of bivariate Granger causality tests. Panel (b) depicts the size of volatility spillovers (in %) between uncertainty and bank stock returns, where a star indicates the net transmitter of volatility.

Table 5.6: Granger causality and directional spillovers by scale and asset allocation II

5.3.4 Uncertainty and bank stocks during COVID-19

In addition to bank asset allocations, extreme market conditions may alter the impact of uncertainty on bank stocks. Beginning in early 2020, the corona crisis affected international financial markets for almost two years. The pandemic-induced uncertainty raised stock market volatility (Jeris and Nath, 2021) and led to a sharp crash of stock prices (Topcu and Gulal, 2020; Al-Awadhi et al., 2020). Acharya et al. (2021) and Dunbar (2021) demonstrate that bank stocks, in particular, are most severely hit by the pandemic compared to non-financial firms. Accordingly, Duan et al. (2021) reveal a sharp increase in systemic risk in the banking sector, where the adverse effects are more pronounced for large and highly leveraged banks. Motivated by these findings, we conduct a sub-sample analysis and restrict our sample to February 1, 2020, until March 31, 2021 (303 observations) to capture the first initial crash of the stock markets and the second wave from November 2020 to March 2021.[5] In fact, the number of U.S. infections and death rates were substantially higher during the second wave, where the number of infections reached an all-time high on January 10, 2021. Based on the sub-sample period, we again assess Granger causality and directional volatility spillover between the uncertainty measures and bank stock returns. The results are depicted in Table 5.7.

		(a) Granger causality				*(b) Spillover*			
	Direction	D1 (2–4)	D2 (4–8)	D3 (8–16)	D4 (16–32)	D1 (2–4)	D2 (4–8)	D3 (8–16)	D4 (16–32)
(I)	VIX → PC1	0.00	0.00	0.00	0.00	21.48⋆	19.35⋆	18.34⋆	9.41⋆
	PC1 → VIX	0.00	0.00	0.01	0.08	14.34	16.51	7.55	6.78
(II)	EPU → PC1	0.05	0.04	0.00	0.00	5.32⋆	4.84⋆	4.11⋆	3.25⋆
	PC1 → EPU	0.48	0.55	0.41	0.82	1.71	1.81	1.00	0.95
(III)	TEU → PC1	0.00	0.04	0.18	0.14	21.72⋆	18.10⋆	12.25⋆	8.14⋆
	PC1 → TEU	0.01	0.12	0.19	0.14	6.34	5.78	5.75	1.46

This table shows causality between uncertainty and bank stock returns (PC1) from February 1, 2020, to March 31, 2021. Panel (a) depicts the p-value of bivariate Granger causality tests. Panel (b) depicts the size of volatility spillovers (in %) between uncertainty and bank stock returns, where a star indicates the net transmitter of volatility.

Table 5.7: Granger causality and directional spillovers during COVID-19

The Granger causality results are similar to the results of the overall period from 2012 to 2022. However, the main and important difference is that EPU also Granger causes bank

[5] For details on the evolution of the pandemic in the banking sector, see Bales and Burghof (2022).

returns in the short run. This implies that the markets care about the uncertainty related to short-run policy responses, such as the introduction of governmental financial support, contact restrictions, or vaccination strategies, to migrate the possible damage to the economy. Twitter-based uncertainty, again, affects stock prices in the short horizon only, but to a much higher extent in terms of volatility spillovers. During COVID-19, the short-run spillovers from TEU to bank returns are 21.72%, while the spillovers over 2012–2022 are 6.22%. Economically, the extraordinarily high levels of pandemic-induced uncertainty led to a large number of tweets, which fueled investor fears and amplified the selling of stocks. The decline of stock prices, in return, enhanced the level of TEU, establishing a short-run nexus between both variables. Figure 5.8 in the Appendix illustrates the crash and recovery of stock prices for the 22 banks in the sample. Finally, we find heavy spillovers between VIX and bank stocks for almost all time horizons. Overall, our findings support the study of Chatterjee and French (2022) and French (2021), who indicate that the markets are more sensitive to Twitter-based uncertainty during the pandemic.

5.3.5 Robustness of the results

A series of alternative specifications are estimated to assess the robustness of the results. First, we replace the Twitter-based uncertainty indicator with two alternative versions: We consider a weighted TEU index, which takes the number of re-tweets and interactions into account (TEU_W). By this, the tweets of influential users, like politicians or celebrities, are given a higher weight. A series of studies shows that tweets of Donald Trump, for example, have a large impact on the financial markets, more than that of normal Twitter users (Pham et al., 2022; Klaus and Koser, 2021). This also raises the potential issue of market manipulation due to single Twitter users. However, Table 5.8 shows that the results for the weighted and unweighted TEU index lead to the same time-frequency conclusions. Hence, putting more weight on influential Twitter users does not bias the results. This may also root in the fact that we consider the first principal component, which eliminates idiosyncratic variation. Moreover, we replace the U.S.-based TEU measure with a TEU index, which is not restricted to the United States and considers all English-speaking tweets (TEU_E). This is important, as cross-country transmissions of EPU may bias the stock market response in the United States (Baker et al., 2021). Table 5.8 also reveals that the results are robust against this alternative specification. Finally, we employ Twitter-based market uncertainty (TMU) of Baker et al. (2021) as an alternative measure. As Table 5.8 indicates, TMU exhibits almost the same dependency structure as the TEU. Specifically, Twitter-based market uncertainty Granger causes bank returns mainly in the short run. Likewise, we observe large volatility spillovers for the same horizon. Hence, this supports our previous findings that social media-derived measures are mainly important in the short run. Second, we replace the first principal component of bank stock returns with an arithmetic average of returns (μ_{Bank}). Thereby, we consider bank-specific shocks and do not focus on the commonality in bank returns. Looking at the causality and spillover effects, this specification makes little qualitative difference to the conclusions of this paper (Table 5.8). Economically, this implies that bank-specific variations, i.e. the idiosyncratic part in bank stock returns, are only marginally impacted by uncertainty.

		(a) Granger causality				*(b) Spillover*			
		D1	D2	D3	D4	D1	D2	D3	D4
	Direction	(2–4)	(4–8)	(8–16)	(16–32)	(2–4)	(4–8)	(8–16)	(16–32)
Replacing TEU by alternative versions									
(I)	$TEU_W \rightarrow$ PC1	0.02	0.02	0.08	0.19	6.20⋆	4.41⋆	4.23⋆	1.11
	PC1 $\rightarrow TEU_W$	0.01	0.08	0.17	0.23	3.73	2.12	1.62	2.05⋆
(II)	$TEU_E \rightarrow$ PC1	0.02	0.01	0.06	0.14	7.22⋆	4.11⋆	4.95⋆	2.11⋆
	PC1 $\rightarrow TEU_E$	0.00	0.04	0.15	0.20	3.03	2.11	1.41	1.96
(III)	TMU $\rightarrow$ PC1	0.00	0.04	0.09	0.23	8.24⋆	5.87⋆	2.42⋆	1.12⋆
	PC1 $\rightarrow$ TMU	0.05	0.22	0.58	0.48	4.78	2.14	1.33	0.21
Replacing PC1 by an average of bank returns									
(IV)	VIX $\rightarrow \mu_{Bank}$	0.02	0.02	0.03	0.01	8.54⋆	7.21⋆	7.03⋆	6.18⋆
	$\mu_{Bank} \rightarrow$ VIX	0.01	0.00	0.03	0.09	6.34	7.13	4.32	1.12
(V)	EPU $\rightarrow \mu_{Bank}$	0.22	0.12	0.05	0.03	0.21	1.23	2.89⋆	2.93⋆
	$\mu_{Bank} \rightarrow$ EPU	0.25	0.10	0.13	0.07	0.98⋆	1.35⋆	0.87	1.69
(VI)	TEU $\rightarrow \mu_{Bank}$	0.01	0.00	0.08	0.09	7.81⋆	5.90⋆	4.12⋆	1.28
	$\mu_{Bank} \rightarrow$ TEU	0.00	0.08	0.14	0.11	4.58	2.89	1.21	1.88⋆

This table shows causality between uncertainty and bank stock returns (PC1) using alternative specifications. Specification (I) employs influence-weighted Twitter uncertainty, while (II) considers all English tweets and is not restricted to the U.S. (III) considers Twitter-based market uncertainty. Specifications (IV)–(VI) use an arithmetic mean of bank returns instead of the first principal component.

Table 5.8: Application of alternative measures

Third, we specify the directional spillovers for forecast horizons of $H = \{5, 6, 7, 8, 9\}$ trading days. The estimation results are almost identical to the effects derived for a horizon of 10 trading days. Finally, we restrict our analysis to the time domain and do not consider

Maximal Overlap Discrete Wavelet Transform before the application of Granger causality and the computation of spillover effects. Table 5.9 in the Appendix shows a two-way relation between VIX and PC1 and a unidirectional impact from TEU to PC1, assuming a 5% level. The multi-scale results, however, highlight that EPU still matters in the medium run, while the effect of TEU is restricted to the short run. This ultimately highlights the informational gain of applying wavelet transformation.

5.4 Conclusion

This study analyzes if the source of uncertainty (newspaper, Twitter, financial market) matters in its impact on U.S. bank returns. The use of Principal Component Analysis shows that financial (VIX), newspaper (EPU), and Twitter-based uncertainty (TEU) share a common variation of 82%, while differing in their exposure to the second principal. This heterogeneity in the uncertainty measures explains its different impact on the stock market. While TEU Granger causes U.S. bank returns in the short run, policy uncertainty is important in the medium run. Hence, the political environment and related uncertainty are important risk factors for the banking sector in the medium rather than short horizon. Moreover, we find evidence of two-way causality between TEU/VIX and bank stocks, considering a horizon of 2–8 trading days. This indicates that turmoil in the banking sector results in a higher amount of tweets, which, in return, affects the markets again due to a higher degree of uncertainty. The calculation of directional volatility spillovers confirms the observed results and provides evidence that Twitter-based uncertainty is an important risk factor in the short run. Overall, VIX is the most important factor. Finally, the impact of uncertainty on bank returns is stronger during the COVID-19 pandemic and for banks with a high ratio of loans to total assets and large off-balance-sheet activities. Economically, banks with a higher loan-to-total assets ratio likely face a higher level of credit risk, which ultimately alters the elasticity of bank stocks to uncertainty shocks. Accordingly, larger off-balance-sheet activities make banks more vulnerable to financial shocks. In contrast, we do not find divergent impacts for banks differing in their fraction of equity capital and the ratio of sovereign securities to total assets. This information is important for financial regulators and policymakers. If policymakers have a better understanding of how uncertainty shocks are transmitted across different frequencies (short, medium, and long run), they could react more effectively to stabilize the financial system. Exemplarily, they could put restrictions on off-balance-sheet activities or implement a clear and open communication strategy to reduce uncertainty and reassure the markets.

5.5 Appendix

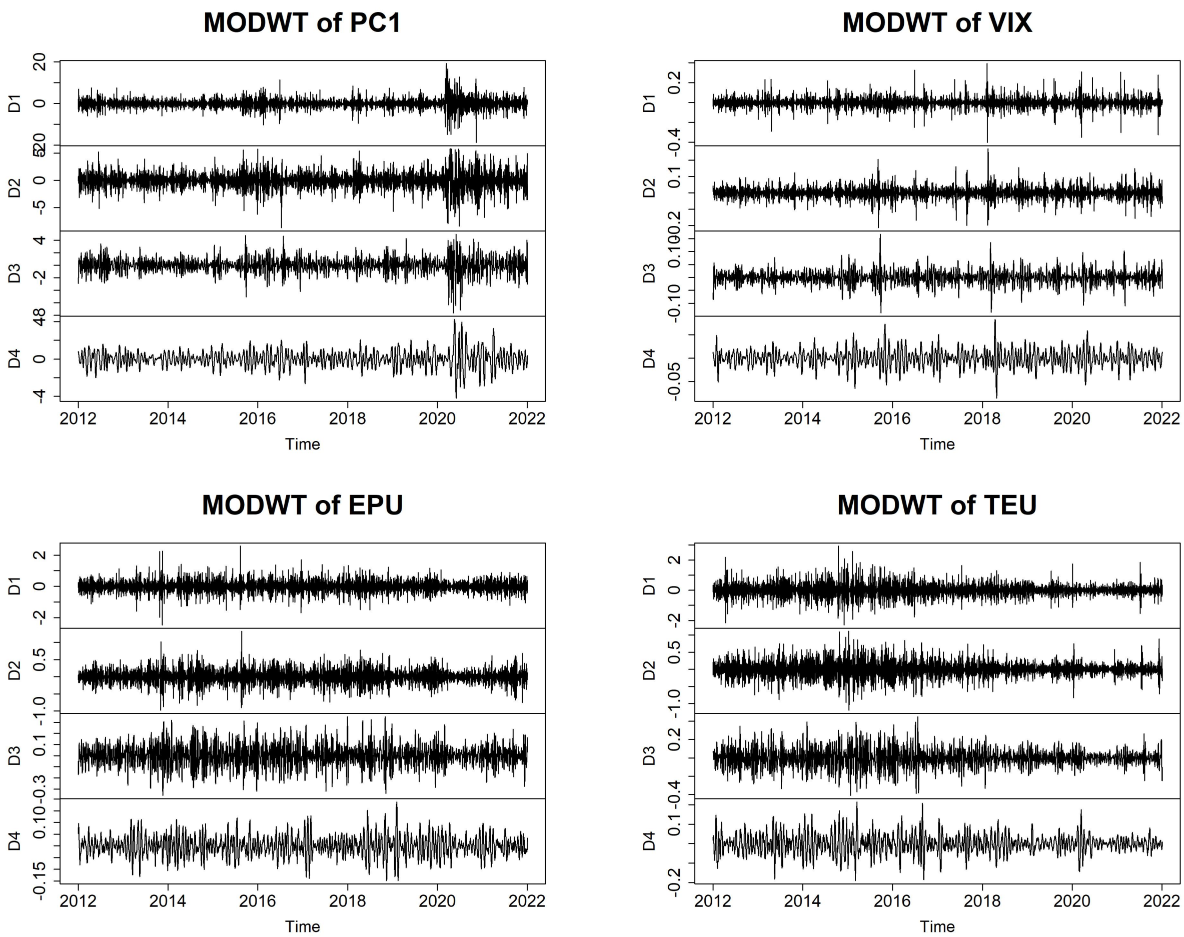

Figure 5.5: Wavelet decomposition of uncertainty measures and bank stock returns

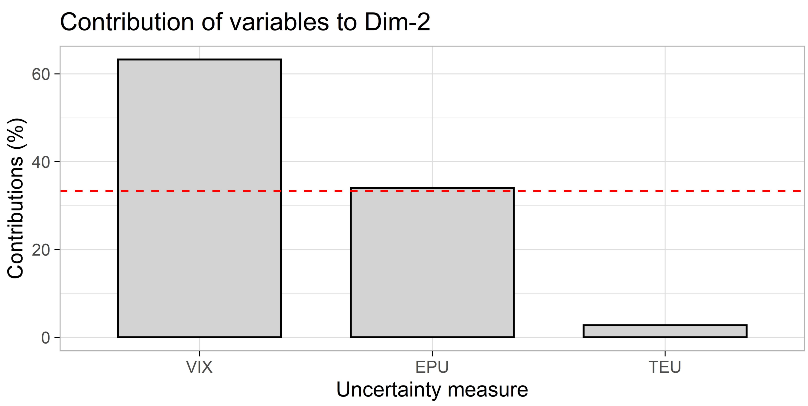

Figure 5.6: Contribution of the uncertainty measures to the second principal component

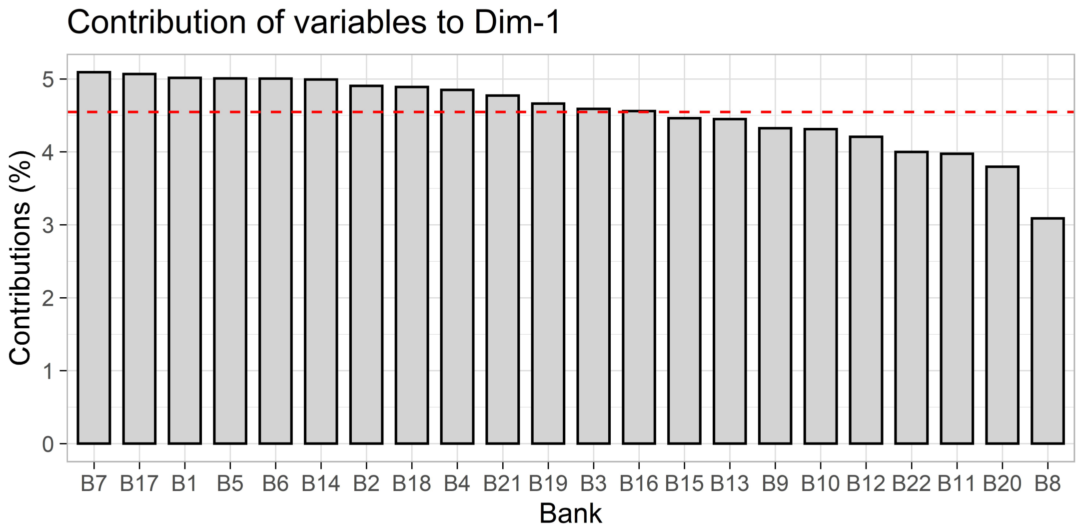

Figure 5.7: Contribution of banks to the first principal component

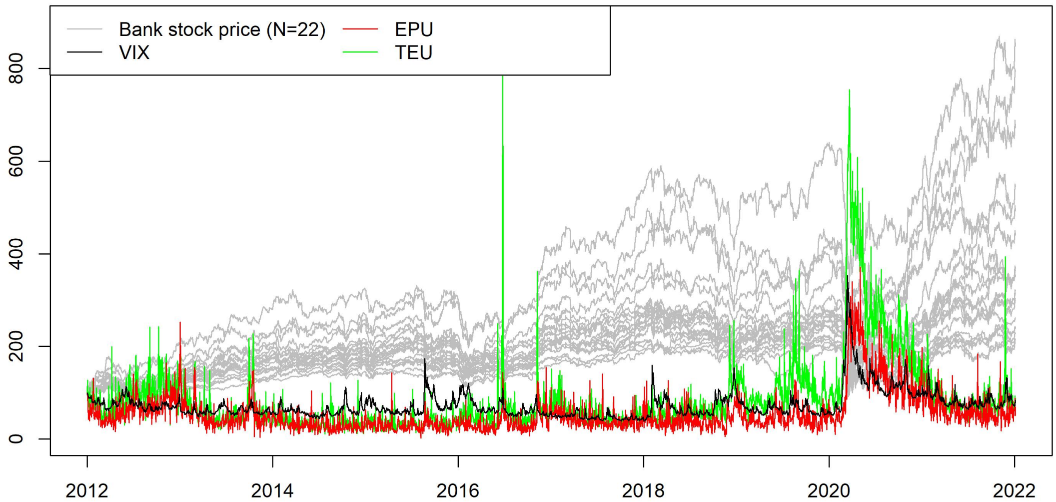

Figure 5.8: Development of individual bank stock prices and uncertainty.

All variables are normalized to 100 in January 2012. The peak of TEU corresponds to the election of Donald Trump in 2016.

	Direction	*(a) Granger causality*	*(b) Spillover*
(I)	VIX $\rightarrow$ PC1	0.00	9.47*
	PC1 $\rightarrow$ VIX	0.03	5.43
(II)	EPU $\rightarrow$ PC1	0.08	0.93*
	PC1 $\rightarrow$ EPU	0.19	0.42
(III)	TEU $\rightarrow$ PC1	0.05	5.19*
	PC1 $\rightarrow$ TEU	0.07	3.94

This table shows causality between uncertainty and bank stock returns (PC1) in the time dimension. Panel (a) depicts the p-value of bivariate Granger causality tests. Panel (b) depicts the size of volatility spillovers (in %) between uncertainty and bank stock returns, where a star indicates the net transmitter of volatility.

Table 5.9: Granger causality and directional spillovers in the time domain

Chapter 6

Overall conclusion

This dissertation sheds light on the main characteristics of sovereign-bank risk contagion and the importance of (policy) uncertainty and interest rates in shaping this dependence. To this end, the thesis addresses various methodological approaches and research questions in four self-contained yet interrelated chapters. This approach ensures robust results and conclusions, as each study serves as a qualitative robustness check for the others.

The first study in Chapter 2 examines the cross-country contagion of sovereign and bank default risk between 2009 and 2021 to evaluate the introduction of the European Banking Union in 2014. Based on daily Credit Default Swap premia of systemically important eurozone banks in 10 countries, the study combines wavelet methods with standard econometric tools: In a first step, the individual CDS series are decomposed into multi-horizon components using discrete wavelet transformation. Second, Granger causality is applied to derive directional network structures between sovereigns and banks for each time horizon. Third, the network links are weighted by the spillover index of Diebold and Yılmaz (2014) to capture the strength of the risk dependence. This process involves estimating 6,840 weighted sovereign-bank linkages for different horizons. The resulting network statistics provide evidence that the introduction of the Single Supervisory Mechanism, as part of the European Banking Union, has been effective in reducing overall financial contagion in the short run (up to 1 month). However, the default risk dependence remains pronounced in the long run. Economically, sovereigns and banks are indirectly linked through the domestic economy. If the sovereign creditworthiness declines, the domestic economy is likely to suffer from poorer public services, higher taxation, increasing cost of capital, and deterioration of bank asset quality. These indirect linkages persist in the long run. Nevertheless, a shock in sovereign or bank risk is less severely transmitted to other eurozone countries, indicated by lower volatility spillovers. Thus, the introduction of the Banking Union supports financial stability by weakening the strength of dependence rather than eliminating the dependence itself. Understanding the frequency structure of contagion can be crucial for policymakers to respond more effectively in their policy-making. The findings are supported by the COVID-19 pandemic. Although the network connectivity increased, the strength of the default risk spillovers remained low over 2020–2021. The network structures and results are robust against several financial control variables.

The second study in Chapter 3 addresses the domestic sovereign-bank dependence and explores potential drivers of this nexus. Based on 48 banks in 14 countries, the study specifies dynamic correlations between sovereign and (joint) banking sector risk in a country using the DCC-GARCH framework of Engle (2002). The estimates reveal that the correlation is significantly higher in eurozone countries and financially distressed economies, such as Italy, Spain, and Portugal. These findings are in line with Chapter 2, where the center of the sovereign-bank risk network is characterized by banks located in Italy, Spain, and Portugal. The countries came to be known during the European debt crisis when a wave of financial contagion after the economic downturn in Greece threatened the survival of the euro area. The lowest risk correlations are observed in Sweden, Denmark, and the United States. This indicates a systematic eurozone risk factor rooted in the home bias of domestic sovereign bond holdings of eurozone banks. To address this bias, the European Union should explicitly introduce disincentives against highly concentrated sovereign exposures. The findings also support the risk-shifting hypothesis of Uhlig (2014), who argues that the European monetary union implicitly shifts sovereign default risk onto the balance sheet of the ECB and other member states. Furthermore, fixed effect panel regressions provide evidence that the sovereign-bank correlation increases in times of great (European) policy uncertainty, high interbank market rates, low bank lending margins, and a low ratio of core bank capital. Economically, banks with a low level of core equity capital relative to their total risk-weighted assets are less likely to withstand shocks to their balance sheets. As a result, the higher risk of a poorly capitalized banking system spills over to the state and results in a closer risk dependence. Moreover, banks charge each other higher rates for unsecured short-term lending in times of financial distress. As revealed by the regression results, these bank liquidity issues and lending aversion in the interbank market are transmitted to other domestic banks and ultimately to the sovereign. In contrast, the slope of the yield curve, the growth rate of the monetary base in the eurozone, and the ratio of variable bank loans to overall loans do not play a significant role in explaining the nexus. The findings are robust against different specifications and a series of macroeconomic and financial control variables. Overall, Chapter 3 emphasizes the importance of bank capital adequacy regulations and joint European policies to mitigate domestic sovereign-bank dependencies.

Building on the results in Chapter 3, the study in Chapter 4 takes a closer look at the impact of economic policy uncertainty on the domestic sovereign-bank dependence by employing continuous wavelet tools. This methodological setting allows for the analysis of causal lead-lag dependencies between sovereign and bank risk on a monthly basis, offering informational advantages over the panel regression conducted in Chapter 3. Considering 32 banks in 10 countries, the study estimates risk-adjusted CDS premia to evaluate the fundamental co-movement between sovereign and bank risk, above what is driven by the financial markets. The use of unadjusted CDS spreads could be misleading, as periods of high market volatility tend to increase the co-movement. The computation of the wavelet coherency, as a measure of correlation, shows that the sovereign-bank dependence significantly tightens in times of political turbulence, such as after the Italian parliament election in 2018 or the Brexit referendum in 2016. Once the influence of policy uncertainty on sovereign and bank risk is eliminated, the partial coherency indicates that the dependence considerably weakens. The computation of lead-lag relationships provides further evidence about the direction of causality. While a higher level of sovereign default risk leads to an increase in bank risk in the short term, the causality reverses in the medium horizon (6–32 months) and bank default risk determines sovereign risk. The results are significant at a level of 5%. Overall, the study provides empirical evidence that political risk factors play an important role in shaping the sovereign-bank risk loop.

The final part of this thesis focuses on different sources of uncertainty and their impact on banks in the United States. As policy uncertainty is identified as a risk factor for sovereigns and banks in Chapter 3 and Chapter 4, the study in Chapter 5 specifically distinguishes between different sources of uncertainty. While newspaper-based policy uncertainty reflects individual opinions of experts or journalists, two alternative uncertainty measures are considered. First, the CBOE volatility index captures the 30-day ahead implied volatility of options written on the S&P500. Second, the Twitter-based economic uncertainty index (TEU) of Baker et al. (2021) represents the beliefs of a large cross-section of social media users. Based on stock returns of the 22 largest U.S. banks, the study specifies Granger causality and financial volatility spillover between uncertainty and (non-idiosyncratic) bank returns across different horizons. The results provide evidence that newspaper-based and Twitter-based uncertainty capture different sources of investor perception in the very short horizon (up to 1 week). Although both measures are correlated, a higher level of Twitter uncertainty negatively affects bank stocks in the short run, while newspaper-based uncertainty becomes relevant in the medium run. Financial market uncertainty is the most important risk factor for banks. Moreover, the study considers the asset allocation of the banks in the sample to infer whether these characteristics alter the impact of uncertainty on bank returns. The causality and volatility spillover estimates demonstrate that the impact of uncertainty is stronger for banks with a high ratio of loans to total assets and large off-balance-sheet activities, measured by the ratio of derivatives to total bank assets. Although credit derivatives are important for securitizing and hedging credit risk, the results reveal that derivatives may also destabilize banks in terms of a higher uncertainty exposure. Moreover, banks with a greater loan ratio likely face a higher level of credit risk, which alters the elasticity to uncertainty shocks. Finally, banks exhibited greater sensitivity to uncertainty during the COVID-19 pandemic. Assuming that bank risk can be transmitted to the state via the sovereign-bank nexus, the results emphasize the importance of differentiating between the source of uncertainty to evaluate its relevance for financial stability. The findings also highlight the growing influence of social media on the financial markets.

Overall, this dissertation highlights the importance of regulatory frameworks, the interest rate environment, and different sources of uncertainty in shaping risk dynamics between sovereigns and banks. The application of wavelet techniques captures the changing nature of these connections across different time scales, thereby enhancing the understanding of the underlying mechanisms driving sovereign and bank risk dynamics. The results of this thesis offer significant implications for policymakers and pave the way for further research. Policymakers can contribute to reducing the transmission of risks between sovereigns and banks by promoting transparency, predictability, and stability in these areas. In addition, continuous vigilance and ongoing efforts to monitor and address potential risks within the financial system are needed since the introduction of the Banking Union does not eliminate but rather weakens risk dependencies in the long run. Given the specific context of the eurozone, the issue of sovereign and bank dependence remains a critical concern. Not least the COVID-19 pandemic has highlighted the (increasing) exposures of banks to sovereign bonds/risk. Going forward, there are promising opportunities for further research in this area. Exploring the impact of other macroeconomic factors on the connectivity between sovereign and bank default risk can provide a more comprehensive understanding of the complex relationship. In addition, examining the evolution and interaction of sovereign and bank risk in times of high inflation and rapidly rising policy rates can contribute to preserving financial stability.

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