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List of Acronyms

AG-DCC Asymmetric Generalized Dynamic Conditional Correlation

CCyB countercyclical capital buffer

CEE Central East European

DCC-MIDAS Dynamic Conditional Correlation - Mixed Data Sampling

EA euro area

ESRB European Systemic Risk Board

FSC Financial Stability Committee

GARCH Generalized Autoregressive Conditional Heteroskedasicity

GARCH-DCC GARCH Dynamic Conditional Correlation

GFC Global Financial Crisis

NII net interest income

NIM net interest margin

OIS Overnight Index Swap

ROA return on assets

ROE return on equity

SDC Sovereign Debt Crisis

VAR vector autoregression

Chapter 0

Introduction

Several crises of the early 21st century have painfully demonstrated the vulnerability of the financial system. During the Global Financial Crisis (GFC), distortions in the US real estate market via systemic effects spilled over to the European financial sector. The European Sovereign Debt Crisis (SDC) has unequivocally highlighted the problem of a common currency in tandem with national fiscal policies. The public and market participants raised questions about the preservation of the euro area (EA) and the stability of the banking sector. In the aftermath of these crises, the ECB decreased key interest rates and kept them at a very low level for an entire decade. Long-term interest rates were lowered sustainably by implementing asset purchase programs. The COVID-19 crisis reminded us that exogenous shocks can also jeopardize financial stability, as demonstrated by a drastic slump in stock prices and a sudden increase in volatilities.

The central research questions of this thesis are closely related to the shock absorption capacity of banks and the financial system. Regulatory issues are discussed on the one hand, and the status quo is examined on the other through different perspectives. This thesis is divided in three chapters.

Chapter 1 investigates the use of a macroprudential policy tool introduced as part of the Basel III framework, the countercyclical capital buffer (CCyB). In times of crisis, the capital buffer is intended to cushion losses caused by adverse market developments and loan defaults. Due to systemic effects, the resilience of individual institutions makes the entire banking and financial system less susceptible to crises. During the GFC, distortions in the financial sector had strong negative effects on real economic activity. For this reason, it should be emphasized that macroprudential measures can not only increase the resilience of the banking sector but also reduce risks to the real economy. In Europe, decision makers have used the CCyB to varying degrees in the past. This heterogeneity in the application of this instrument raises questions against the background that all countries should strive to increase the resilience of the financial system. Chapter 1 empirically examines the institutional, financial, and economic variables that explain differences in the use of this macroprudential instrument. The analysis is based on the framework that serves as the guidance for determining the capital buffer. The empirical results allow us to critically examine the application of the capital buffer in Europe.

Managing risk positions is crucial to comply with regulatory capital requirements. In the long term, banks can increase capital ratios by generating profits and allocating them to their capital reserves. Thus, banking sector profitability could be relevant to financial sector stability in the long run. In the light of the low interest rate environment, it is informative to revisit the relationship between interest rates and bank profitability. Chapter 2 examines how changes in the interest rate structure affect the market value of banks which serves as a proxy for the expectation of future profitability. More precisely, the chapter analyzes the reactions of European bank stock prices to changes in market interest rates during ECB monetary policy announcements. Since interest rates play a major role in the business model of banks, the study investigates whether bank stocks react systematically differently to changing market interest rates during central bank announcements than other stocks. An adequate understanding of the transmission of interest rate changes is a necessary condition for an appropriate evaluation of interest rate risks in the financial system.

Chapter 3 investigates the correlation dynamics of Western and Eastern European stock markets during the early 21st century. Portfolio risk is not only determined by the individual volatilities of the underlying assets, but also by their correlations. The correct assessment of co-movements is therefore important from a systemic point of view. In crisis times, correlations might change dramatically, leading to soaring systemic risk. Since higher correlations can indicate a stronger interconnectedness of economies, the analysis of the co-movements is also relevant to the real economy. Hence, the correlation analysis of the European stock markets can provide valuable information about market fragmentation, especially against the background of the EU enlargement. Dynamic correlations are estimated and underlying reasons for the variation are discussed. The focus is on the market turmoil triggered by the spread of COVID-19.

Chapter 1

How do Regulators set the Countercyclical Capital Buffer?

Abstract

As part of the Basel III regulatory framework, the macroprudential CCyB was introduced to mitigate the pro-cyclicality in the financial system. National designated authorities are supposed to set the CCyB based on a "guided discretion" approach that combines rule-based and discretionary elements. We identify a CCyB puzzle as we do not find the credit-to-GDP gap, the recommended rule-based component of the CCyB, to be crucial for buffer decisions. Instead, designated authorities appear to base their CCyB decisions in a systematic way on the discretionary elements of the framework, namely the development of house prices and non-performing loans. We also find national institutional frameworks to be relevant for CCyB policies.

This chapter is joint work with Bernhard Herz. A version of this chapter is published as Herz and Keller (2023) available at `https://www.ijcb.org/journals/index.htm`. I declare that I contributed significantly in all relevant areas (conception, empirical analysis, drafting of the manuscript, revisions). We would like to thank Cyril Couaillier, Matthias Köhler, Yves Schüler, and, in particular, an anonymous referee for very helpful comments.

1.1 Introduction

In times of financial stress, the procyclical behavior of banks is likely to generate substantial negative feedback effects on the real economy. As asset prices decline, capital positions deteriorate, pressure on margins and lending standards increases, and financial institutions restrict lending to deleverage (Brunnermeier, 2009). The European Systemic Risk Board (ESRB) points out that the subsequent credit shortage aggravates the economic slowdown, with negative repercussions on banks' credit portfolios (ESRB, 2014). Since most banks are both creditors and debtors, network effects are likely to emerge that threaten the stability of the financial system (Brunnermeier, 2009).

To work against such vicious circles, the CCyB was introduced as part of the global regulatory Basel III framework after a lot of preparatory work. It "is designed to help counter pro-cyclicality in the financial system. Capital should be accumulated when cyclical systemic risk is judged to be increasing, creating buffers that increase the resilience of the banking sector during periods of stress when losses materialise" (ESRB, 2014). Accordingly, the CCyB should fluctuate over the financial cycle and be fully loaded at the onset of financial crises and economic downturns.

National designated authorities are supposed to implement the CCyB under a "guided discretion" approach, which combines rule-based and discretionary elements. As the rule-based component, the so-called buffer guide is based on the credit-to-GDP gap, i.e., the deviation of the credit-to-GDP ratio from its long-term trend (ESRB, 2014; Basel Committee on Banking Supervision, 2010). The discretionary component involves additional categories of indicators such as credit developments and private sector debt burden. These risk indicators are not specifically defined and are not subject to a specific rule so that ESRB member countries have considerable leeway in their CCyB policies.

ESRB members have used this regulatory space to a remarkable degree. On the one hand, most authorities in southern Europe (e.g., Spain, Italy, Greece, Portugal) seem to have followed ESRB recommendations and kept CCyB rates at zero, consistent with negative credit-to-GDP gaps on the national level. On the other hand, most northern European countries (e.g., Sweden, Norway, Denmark) implemented more ambitious policies and set higher CCyB rates than required by national buffer guides[1] (see figure 1.1). Also, in communicating their CCyB decisions, national authorities' policies revealed a remarkable heterogeneity in how they implemented the ESRB framework on the national level.

Given that the Basel III framework has been put in place in many countries, it is time to analyze to what extent regulators actually follow these provisions. Such an analysis is particularly important given the intense discussion of the framework and the role of the credit-to-GDP gap as the central measure of systemic risks (see, e.g., Borio et al. (2010), Gischer et al. (2019)).

Given the wide gap between the Basel III and ESRB recommendations on the one hand and the actual CCyB policies in EU Member States, on the other hand, we are interested in the key motives for national CCyB decisions. We contribute to the sparse literature on the CCyB instrument by empirically analyzing the actual drivers of CCyB decisions in European countries. In this analysis, we differentiate two dimensions of the CCyB, which are related but might be driven by different determinants. First, we address in a qualitative analysis whether or not national designated authorities make use of the countercyclical buffer. Second, we analyze the factors driving CCyB decisions over time. Both approaches provide interesting complementary information in order to better understand macroprudential policies in the EU.

In contrast to its prominent role in the ESRB (2014) recommendation, we do neither find robust empirical evidence that the credit-to-GDP gap systematically

[1] Our analysis is limited to the period up to and including 2019, i.e., before the outbreak of the coronavirus pandemic. Since then, most Member States have released the capital buffer.

drives the buffer activation nor its variation over time, as the coefficients of the credit-to-GDP gap are not significantly different from zero. We also test the hypothesis of designated authorities following the rule-based component of the ESRB (2014) recommendation, where the CCyB is calibrated to the credit-to-GDP gap. This alternative null hypothesis is clearly rejected. Interestingly we also do not find the selected buffer guides to be crucial for CCyB decisions.

In contrast, higher house price growth and lower non-performing loans ratios make the use of the countercyclical buffer more likely. We also find evidence that developments in house prices and credit quality are relevant for CCyB adjustments over time. Thus, additional risk indicators appear to be more relevant for CCyB decisions than the credit-to-GDP gap.

Consistent with Edge and Liang (2020), we find that the institutional role of the designated authority matters. The likelihood of using the CCyB is smaller if the existing prudential regulator or the central bank takes the final decision about the buffer. In contrast, the announcement of a positive countercyclical buffer is more likely if the domestic Financial Stability Committee (FSC) is the decision-maker.

In line with the literature, we argue that the weak relationship between the credit-to-GDP gap and actual CCyB decisions is a major challenge for the communication and the acceptance of the macroprudential instrument.

We do not claim that the credit-GDP gap is not considered at all by national authorities. However, it does not seem to be systematically taken into account in decision-making. Against the background of its highlighted importance the gap takes in official recommendations and European legislation, the results raise the question of whether the indicator is suitable for setting the buffer at all.

The remainder of this paper is organized as follows: Section 1.2 discusses the concept of "guided discretion" as implemented in the CCyB context and reviews the literature. Section 1.3 presents the data used in our empirical investigation. In section 1.4, we discuss our model selection and the results of the logit and linear panel regression. Section 1.5 provides several robustness checks. Finally, section 1.6 concludes.

1.2 Guided Discretion

To stabilize the financial sector, the ESRB requires designated authorities to impose a capital buffer on credit institutions and relevant investment firms (Directive 2013/36/EU, 2013) based on a "guided discretion" approach that combines rule-based and discretionary elements. This CCyB rate ranges from 0% to 2.5% of risk-weighted assets, in steps of at least 0.25 percentage points. As the rule-based element, the so-called benchmark buffer rate requires a 0% capital buffer for credit-to-GDP gaps below 2 percentage points, a linearly increasing rate ranging from 0% to 2.5% for credit-to-GDP gaps between 2 percentage points and 10 percentage points, and a top 2.5% CCyB rate if the corresponding ratio is more than ten percentage points above its long-term trend (ESRB, 2014)(see equation 1.1 and figure 1.1).

$$\text{Benchmark buffer rate}_t(\%) = \begin{cases} 0 & if \quad Gap_t \leq 2pp \\ 0.3125 * Gap_t - 0.625 & if \quad 2pp < Gap_t < 10pp, \\ 2.5 & if \quad Gap_t \geq 10pp \end{cases} \tag{1.1}$$

Concerning the discretionary component the ESRB (2014) suggests complementing the credit-to-GDP gap by several additional variables[2] to gauge the build-up of systemic risk,

(a) *potential overvaluation of property prices*

[2]Among BIS Member States, designated authorities in Germany take into account the largest number of core systemic risk indicators in their CCyB decisions, followed by France and the UK (BIS, 2017). For an extensive discussion of the forecasting quality of the different indicators, see Detken et al. (2014) and Tölö et al. (2018).

(b) *credit developments*

(c) *external imbalances*

(d) *strength of bank balance sheets*

(e) *private sector debt burden*

(f) *potential mispricing of risk*

(g) *model-based risk measures that combine the credit-to-GDP gap and a selection of the above mentioned variables.*

The concept of "guided discretion" is thus specified as "a rules-based approach with the exercise of their discretionary powers when deciding on the appropriate buffer rate" (ESRB, 2014). Although there is scope for national authorities, the credit-GDP gap is formally by far the most important indicator. As the only indicator, the gap is directly and explicitly converted into a buffer guide value (ESRB, 2014). Furthermore, to improve transparency, EU legislation requires national institutions to quarterly publish the credit-to-GDP ratio, the credit-to-GDP gap, and the buffer guide (Art. 136, Directive 2013/36/EU (2013)). In contrast, the ESRB does not impose specific guidelines on how to account for the seven other categories of risk indicators. It is only recommended to publish variables from categories (a) to (f) if they are relevant and available (ESRB, 2014).

Obviously, a necessary condition for a rule-based CCyB framework is the credit-to-GDP gap to be a good predictor of financial crises. Borio and Lowe (2002b) identify the credit-to-GDP gap as the best single indicator among a wide variety of alternative variables. Borio et al. (2010) document for a set of developed countries that pronounced above-trend increases in the credit-to-GDP ratio, i.e., positive credit-to-GDP gaps, typically precede financial crises.

When calculating credit-to-GDP ratios, two elements turned out to be of particular importance, the definition of credit and the trend extraction method to filter out the cyclical component. According to the official recommendation, national designated authorities are supposed to use a "broad measure of the stock of credit" (ESRB,

2014) for computing the credit-to-GDP ratio. Drehmann (2013) uses total credit to the non-financial sector and bank credit for calculating the credit-to-GDP gap. While both aggregates are helpful in constructing early warning tools, he finds the credit gap based on total non-financial sector debt, which is also used in the so-called standardized credit-to-GDP gap, to better reflect the underlying risk preceding financial crises.

On a more technical level, calculating credit-to-GDP gaps involves a number of crucial assumptions on how to decompose the time series into cyclical and trend components. Borio et al. (2010) recommend a high smoothing parameter when estimating the trend of the credit-to-GDP ratio by using a one-sided (i.e., recursive) Hodrick-Prescott (HP) filter to reflect the longer duration of credit cycles compared to business cycles. In particular, they estimate the median of credit cycles to be about 15 years, and therefore, three to four times longer than standard business cycles. Under such a long duration, the corresponding smoothing parameter for quarterly data should be in the range between 125,000 and 400,000 (Borio et al., 2010). The ESRB (2014) follows this literature in recommending a one-sided HP-filter with large smoothing parameter ($\lambda = 400,000$).

In contrast, Edge and Meisenzahl (2011) find that credit-to-GDP gaps are not a reliable basis for determining CCyB rates. In particular, volatile end-of-sample trend estimates may lead to distortions when assessing credit gaps in real-time, and thus, might lead to potential ex-post revisions of the gap. The critique is related to the more general observation that HP-filters are plagued by spurious dynamics. Hamilton (2018) advises to refrain from using HP-filters completely and to use linear projections based on the four most recent values. In contrast, Drehmann and Yetman (2018) recommend the use of HP-filters when estimating credit gaps as none of the considered alternative indicators, i.e., gaps based on linear projections and 20-quarter growth rates, systematically outperform the standard credit-to-GDP gap.

Galán (2019) regards the smoothing parameter of the standardized credit-to-

GDP gap as unrealistically high since he estimates the financial cycle in most European countries to be shorter. The resulting high degree of inertia implies that the standardized gap is a biased signal for the true state of the financial cycle, with recent credit gaps remaining in deeply negative territory. There is more support for using smaller and/or more adjusted smoothing parameters (e.g., Kauko and Tölö, 2019; Wezel, 2019). Reigl and Uusküla (2018) investigate, in particular, the weaknesses of the standardized credit-to-GDP gap. Short time series intensify exceptionally small (i.e., negative) standardized credit gaps so that in some cases, even a pronounced credit boom would not have closed the negative gap (Reigl and Uusküla, 2018).

Wolf et al. (2020) find considerable differences between standard one-sided HP-filters and their corresponding two-sided version. One-sided filters suppress higher-frequency volatility more, which is what should be extracted by the filter. They advise against the standard one-sided HP-filter for extracting cyclical trends in real-time and propose a lower smoothing parameter together with a multiplicative rescaling factor for the cyclical component (Wolf et al., 2020).

As the credit-to-GDP gaps in 2019 (figure 1.1 and equation 1.1) imply, buffer benchmark rates have been zero or very small in most countries. Not surprisingly, the widespread practice of designated authorities to deviate from the benchmark buffer rate has led to an intensive discussion of the ESRB recommendation.

The ESRB (2019, 2020) and Couaillier et al. (2019) emphasize that some national authorities follow more ambitious CCyB policies either by applying more demanding buffer guides or explicitly accounting for additional indicators besides the credit-to-GDP gap. For instance, the UK, the Czech Republic, and Lithuania have implemented a positive "neutral rate", i.e., a positive CCyB rate even when risk is considered to be only moderate (ESRB, 2019, 2020).

In the communiqués that accompany and explain CCyB decisions, national designated authorities provide further insights into their strategies and, in particular, the specific role of rule-based and discretionary elements in their CCyB policies. The Swedish Financial Supervisory Authority, e.g., declares to place *"little weight on the buffer guide as an indicator to raise the buffer since the underlying trend in lending in relation to GDP deviates significantly from a level that is sustainable in the long run. Other authorities with responsibility for macroprudential tools also place little weight on the buffer guide and look at other indicators"* (Finansinspektionen, 2018). The BaFin (2019) as Germany's designated authority mentions three risk categories, namely economic risk, real estate risk, and interest rate risk, by citing the recommendation of the domestic Financial Stability Committee when activating the CCyB in 2019. The BaFin (2019) further concludes that additional variables mentioned in ESRB (2014) signal the build-up of cyclical risk, e.g., developments in real estate prices, growth in housing loans, and credit growth to non-financial corporations. When activating the CCyB, the Czech National Bank (2015) indicated that the credit-to-GDP gap is not fully suitable for CCyB rate decisions in the Czech Republic and that it takes into account other indicators that better reflect the so-called converging economy. The decision to increase the buffer is primarily justified by increased credit growth. Moreover, the debt-to-income ratio, credit standards, and the property markets are also mentioned as important factors (Czech National Bank, 2015).

Not so surprisingly, national decision-makers whose capital buffer decisions are more in line with the buffer benchmarks also give more weight to the credit-to-GDP gap in explaining their buffer decisions. For instance, the Banca d'Italia (2019) vindicated her decision to leave the CCyB unchanged at 0% with the standardized and the nationally adjusted credit-to-GDP gap, both of which were in negative territory. In the further step, other indicators are discussed, such as the growth of bank loans, non-performing loans, and the unemployment rate. Similarly, the Banco de Portugal (2019) in her decision to leave the CCyB unchanged at 0% firstly addressed the standardized and the nationally adjusted credit-GDP gap and then discussed additional indicators, most of which sent similar signals. In doing so, the national designated authority followed the categories recommended by ESRB (2014) and explained recent developments in credit growth, credit demand and spreads, house prices, the loan-to-deposit ratio, the debt-service-ratio, and the current account balance.

In their policy evaluation Babić and Fahr (2019) discuss how positive CCyB rates in a negative credit gap environment have created major communication challenges for national macroprudential authorities. They find that the credit-to-GDP gap has only a limited impact on CCyB decisions in European countries as national decision-makers rely on alternative measures to identify the state of the financial cycle, e.g., a composite indicator as in Slovakia. As a result, they advocate using additional risk measures consistently. In a rare study of the role of the institutional supervisory framework for CCyB decisions, Edge and Liang (2020) find that institutionally stronger FSCs are associated with a higher likelihood of positive CCyB rates. Their analysis also indicates that the credit-to-GDP gap is not systematically relevant for CCyB decisions.

Given this evidence that the rule-based component of the regulatory framework is only of a minor, if any, relevance for CCyB decisions, the question arises of what actually drives buffer decisions in Europe. To the best of our knowledge, we are only aware of one study that empirically analyzes CCyB decisions. While Edge and Liang (2020) focus on how the institutional design of FSCs affects the initial use of the CCyB, they also control for other economic and financial indicators.[3] They find that most FSCs have relatively weak tools and seem to be motivated by symbolic delegation, i.e., signaling action to the public. The credit-to-GDP gap does not significantly affect the probability of setting positive CCyB rates (Edge and Liang,

[3]Earlier work focuses on a broader set of prudential tools as in Cerutti et al. (2016) and Cerutti et al. (2017), while experience with the CCyB in Europe was very limited. For macroprudential policies in general, Cerutti et al. (2017) and Akinci and Olmstead-Rumsey (2018) analyze the effectiveness of various macroprudential tools.

2020).

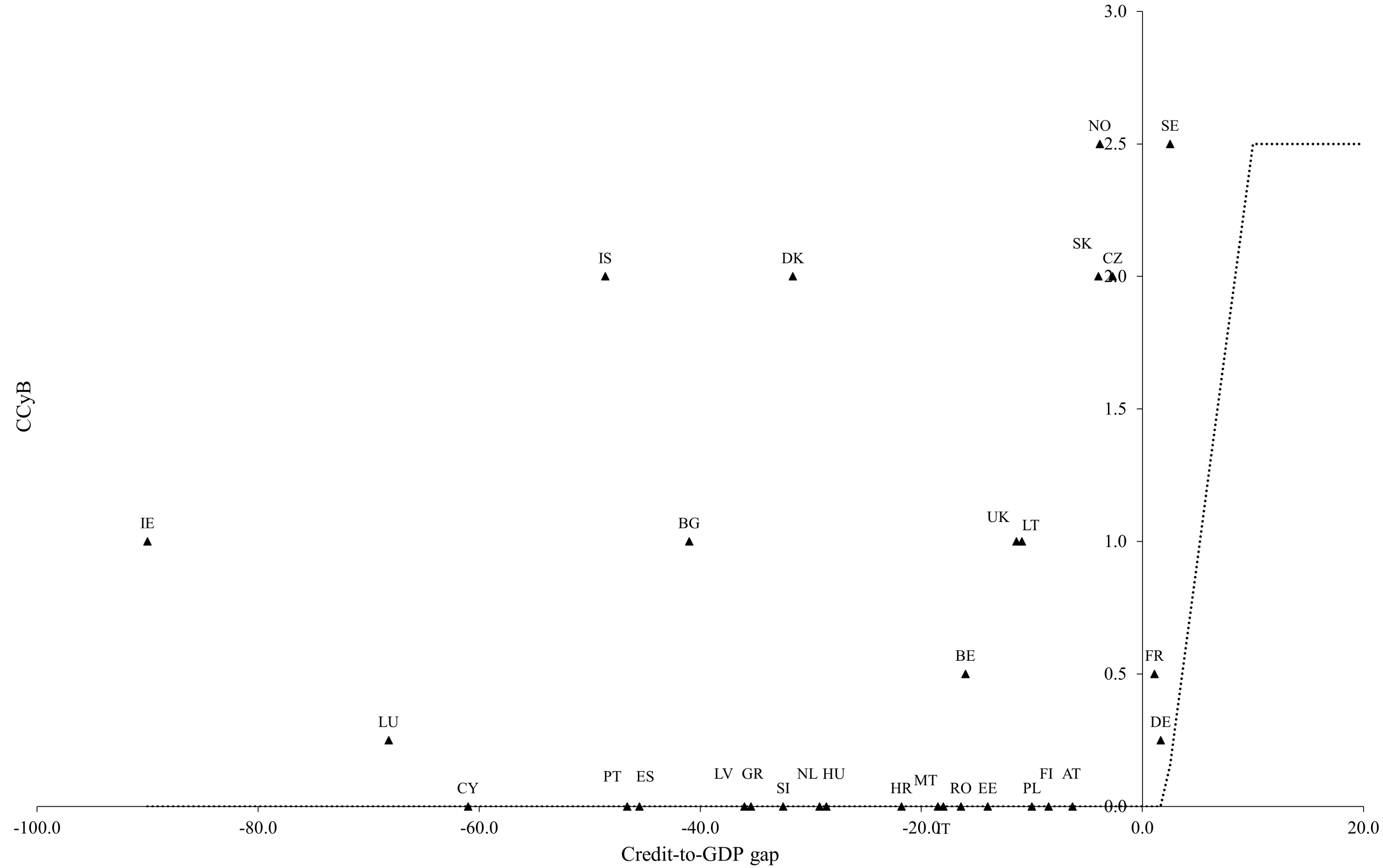


Figure 1.1: Credit-to-GDP gaps and announced CCyB rates.

Notes: Latest available data as per December 2019. All values are reported in percentage points. X-axis: Credit-to-GDP gap. Y-axis: Pending CCyB. The dotted line indicates buffer guides calculated from the rule-based component.

Data Source: ESRB.

1.3 Data

As the ESRB provides the framework for national CCyB decisions[4] we build on the ESRB data set and analyze CCyB policies during the time period between 2014, when the CCyB framework was implemented, to the end of 2019, the time up to the coronavirus pandemic. If there was more than one decision for a particular quarter and country, we kept the last decision. Our panel is unbalanced since designated authorities started to report CCyB decisions at different points in time. If available, the standardized credit-to-GDP data[5] is used in our analysis. In some cases, only measures calculated from narrower aggregates were reported. We include the 30 European countries from the ESRB data set (table 1.8) except Norway, Iceland, and Greece, as comparable data on credit and house price developments were not available.

The ESRB (2014) mentions several complementary risk categories that might indicate the build-up of systemic risk. As additional indicators (see table 1.1 for further details), we approximate the *potential overvaluation of property prices (a)* by the growth rate of the domestic house price index over five years. Even though changes in house prices may be fundamentally justified, real estate prices can add useful information for predicting financial crises (see, e.g., Borio and Lowe (2002a)). The Basel Committee's member countries consider house price growth after credit-to-GDP measures most often for setting the CCyB (BIS, 2017). Accounting for property prices in macroprudential decisions is also in line with Borio (2014), who identifies real estate prices as key drivers for the financial cycle. Moreover, house price index data for European countries is typically available on a quarterly basis with a relatively short time lag. To monitor *credit developments (b)*, we consider the year-on-year

[4]In this paper, we concentrate on the announced (pending, future) CCyB, which has to be fulfilled at the end of the transitional period, which is usually one year. In between, the announced requirement may be different from the effective capital requirement. In this context, the terms "announced", "pending", and "future" are used interchangeably.

[5]We cross-checked ESRB data with data available from national macroprudential/designated authorities and corrected obvious errors.

growth rate of private non-financial sector debt securities and loans. Even though the credit-to-GDP gap is positively correlated with credit growth, some countries exhibit substantial growth rates in debt while having negative credit-to-GDP gaps. We take quarterly current account data (in % of GDP) as a measure for *external imbalances (c)*. To proxy the *strength of bank balance sheets (d)*, we employ both regulatory capital (in % of RWA) and non-performing loans (in % of total gross loans). To measure the *private sector debt burden (e)*, the ESRB (2014) and some national supervisors propose debt-service ratios (Tente et al., 2015). Due to data limitations, we cannot take these into account. To account for *potential mispricing of risk (f)*, we incorporate the year-on-year growth rate of the leading domestic stock market index and the corresponding realized volatility. To have comparable indicators of the domestic stock market volatilities, we calculate the volatility proxy from the quarterly sum of daily squared returns.[6] The ESRB (2014) proposes real equity price growth as a potential variable to measure the mispricing of risk. As pointed out by Tente et al. (2015), strong and sudden price increases in stock markets may indicate that risks are not correctly priced by the market. A number of studies (e.g., Detken et al., 2014; Tölö et al., 2018) found that equity price developments add useful information, in particular in multivariate signaling approaches. Analogously, relatively low equity price volatility may indicate that stock investors underestimate the associated risk (Tente et al., 2015) and may lead to elevated risk-taking (Tölö et al., 2018).

In addition to these macroeconomic and financial variables, we consider several institutional variables to control for differences in national regulatory governance. In investigating the decision to use the CCyB actively, we add indicator variables mirroring the role of the decision-maker, as proposed in Edge and Liang (2020). The dummy variable "PR sets CCyB" equals one if the prudential regulator sets the CCyB and zero otherwise. Accordingly, the variables "CB sets CCyB", "MF sets

[6] In more detail, we follow Christiansen et al. (2012) in defining the realized volatility as $RV_{it} = ln\sqrt{\sum_{s=1}^{Q_t} r_{its}^2}$, where Q_t denotes the number of return observations in quarter t.

CCyB" and "FSC sets CCyB" account for the central bank, the ministry of finance, and the FSC as decision-makers. The FSC consists of multiple institutions and generally includes the central bank, the prudential regulator, and the government (Edge and Liang, 2020). While the committee is the designated authority in a few cases, it has only an advisory role in most member countries. Edge and Liang (2020) show that the focus of existing institutions, e.g., financial soundness on the individual level for the prudential regulator, influences macroprudential decisions. As these institutional variables vary only between countries, but not over time in our estimation period, country fixed effects absorb their influence in the linear panel regression. Table 1.1 describes the time series, transformations and raw data sources. Table 1.2 provides summary statistics and table 1.3 coefficients of correlations for the transformed time series.

Table 1.1: Variable description

Variable	Description	Source
CCyB	Announced (pending) rate of the countercyclical capital buffer (in % of RWA), quarterly, linearly interpolated in case of missing data.	ESRB.
$CCyB^{>0}$	Indicator variable that equals 1 if $CCyB > 0$ and 0 otherwise, derived from CCyB, quarterly.	ESRB.
Credit-to-GDP gap	Credit-to-GDP gap (Deviation of the Credit-to-GDP ratio from its long-term trend), quarterly, linearly interpolated in case of missing data.	ESRB, national authorities.
Credit growth (1Y)	Year-on-year growth rate (in %) of debt securities and loans of the private non-financial sector, quarterly.	ECB.
MFI credit growth (1Y)	Year-on-year growth rate (in %) of MFI credit (loans and debt securities) granted to (domestic) non-financial corporations and households, quarterly.	ECB.
Credit-to-GDP ratio	Credit-to-GDP ratio, quarterly, linearly interpolated in case of missing data.	ESRB, national authorities.
Buffer guide	CCyB guide, quarterly, linearly interpolated in case of missing data.	ESRB.
House prices (5Y)	House price index growth (total, 2015=100) over 5 years, quarterly.	Eurostat.
Stock index (1Y)	Domestic stock market index, year-on-year growth rate of the quarterly mean of daily levels.	Datastream.
Stock index volatility	Realized index volatility (in logs), calculated from daily stock market index levels, quarterly.	Datastream, own calculations.
Current account	Current account (in % of GDP), quarterly.	Eurostat.
Regulatory capital	Regulatory capital (in % of RWA), quarterly, linearly interpolated in case of missing data.	IMF.
Non-performing loans	Non-performing loans (in % of total gross loans), quarterly, linearly interpolated in case of missing data.	IMF.
PR sets CCyB	Indicator variable, equals 1 if the prudential regulator sets CCyB and 0 otherwise.	ESRB, Edge and Liang (2020).
CB sets CCyB	Indicator variable, equals 1 if the central bank sets CCyB and 0 otherwise.	ESRB, Edge and Liang (2020).
MF sets CCyB	Indicator variable, equals 1 if the ministry of finance sets CCyB and 0 otherwise.	ESRB, Edge and Liang (2020).
FSC sets CCyB	Indicator variable, equals 1 if the financial stability committee sets CCyB and 0 otherwise.	ESRB, Edge and Liang (2020).

Table 1.2: Independent variables - summary statistics

Variable	**Abbreviation**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Observations**
Credit-to-GDP gap	Gap	-20.24	19.85	-93.00	13.50	493
Credit growth (1Y)	CG	2.89	4.29	-8.66	44.98	493
MFI credit growth (1Y)	MFI CG	2.13	5.29	-29.78	13.63	454
Credit-to-GDP ratio	Ratio	131.65	60.29	36.20	359.00	493
House prices (5Y)	HP	20.65	19.56	-24.32	92.99	493
Stock index (1Y)	SI	4.82	14.43	-26.81	51.89	493
Stock index volatility	SIV	-2.76	0.41	-3.96	-1.64	493
Current account	CA	1.60	6.98	-45.50	29.90	493
Regulatory capital	RC	19.84	3.48	12.27	36.08	493
Non-performing loans	NPL	5.74	6.52	0.36	47.75	493
PR sets CCyB	PR	0.23	0.42	0.00	1.00	493
CB sets CCyB	CB	0.61	0.49	0.00	1.00	493
MF sets CCyB	MF	0.08	0.27	0.00	1.00	493
FSC sets CCyB	FSC	0.08	0.27	0.00	1.00	493

Notes: Further details on data calculation and sources are provided in table 1.1.

Table 1.3: Correlations of explanatory variables

Variable	Gap	CG	MFI CG	Ratio	HP	SI	SIV	CA	RC	NPL
Gap	1.000									
CG	0.434	1.000								
MFI CG	0.575	0.483	1.000							
Ratio	-0.388	-0.248	-0.459	1.000						
HP	-0.071	0.249	0.314	-0.012	1.000					
SI	-0.008	0.141	0.052	-0.078	0.118	1.000				
SIV	0.119	-0.070	-0.056	0.220	-0.153	-0.182	1.000			
CA	0.014	-0.003	0.080	0.034	0.079	0.032	-0.078	1.000		
RC	0.042	0.128	0.110	0.118	0.382	0.116	-0.189	0.025	1.000	
NPL	-0.373	-0.347	-0.543	0.351	-0.441	-0.125	-0.020	-0.204	-0.278	1.000

Notes: Further details on data calculation and sources are provided in table 1.1.

1.4 Estimation

There are several challenges when empirically investigating CCyB policies. First, the framework of this macroprudential tool has been implemented only recently, and many countries have not actively used the countercyclical buffer yet. Second, the dependent variable CCyB is truncated with a lower bound of CCyB=0% and an upper bound at CCyB=2.5%. Third, the mixture of different starting points of the CCyB reporting and diverse financial structures implies an unbalanced panel in which unobserved heterogeneity is likely to be present.

As discussed above, we differentiate between the decisions to actively use a CCyB, i.e., to announce a non-zero rate, and to set a specific level of the buffer. Obviously, the second decision is contingent on the first.

To examine the first question, i.e., the decision to activate the CCyB, we estimate a random-effects logit model as in Edge and Liang (2020),

$$Pr(CCyB_{it}^{>0}) = \frac{1}{(1 + exp[-(\alpha + \mathbf{x}_{it}'\boldsymbol{\beta} + \mathbf{z}_i'\boldsymbol{\gamma} + \delta_i)])}, \tag{1.2}$$

where $CCyB_{it}^{>0}$ equals one if the buffer is active with a positive announced rate for country i in quarter t and zero otherwise. $\mathbf{x}_{it}$ represents the vector of economic and financial indicators as discussed in the previous section, and $\mathbf{z}_i$ the country-specific indicator variables for the decision-maker. Finally, δ_i denotes the unobserved effect.

As we investigate whether the capital buffer is above zero for a given country and point in time, the dependent variable varies over time and country, in contrast to Edge and Liang (2020) who only examine whether the macroprudential instrument is used or has been used for a given country. Furthermore, we estimate the model based on quarterly data instead of annual data, with missing data being replaced by linear interpolations, if necessary.

Table 1.4 reports the random-effects logit regression results. We do not find reliable empirical evidence for a substantial role of the credit-to-GDP gap for CCyB policies in Europe. This is obviously at odds with the prominent role of the rule-based component in the ESRB recommendation. It also reflects the weak relationship of the credit-to-GDP gap and the buffer rate, as displayed in figure 1.1.

To better understand the guided discretion approach proposed by the ESRB, we examine the (non) role of the credit-to-GDP gap in greater detail. As specified by equation 1.1, designated authorities are expected to activate the CCyB as soon as

Table 1.4: Random-effects logistic regression

$CCyB^{>0}$	I	II	III	IV
Credit-to-GDP gap	0.0870	0.1061*	0.0932	0.0857
	(0.0595)	(0.0574)	(0.0736)	(0.0582)
Credit growth (1Y)	-0.2268	-0.2211	-0.2577	-0.2219
	(0.1489)	(0.1519)	(0.1645)	(0.1514)
House prices (5Y)	0.3360***	0.3594***	0.3868***	0.3567***
	(0.0472)	(0.0461)	(0.0558)	(0.0460)
Stock index (1Y)	-0.0488	-0.0451	-0.0464	-0.0470
	(0.0349)	(0.0352)	(0.0377)	(0.0350)
Stock index volatility	0.8988	1.1637	1.1349	1.0075
	(1.2663)	(1.3089)	(1.3855)	(1.2878)
Current account	0.0020	0.0041	0.0079	0.0002
	(0.0549)	(0.0561)	(0.0611)	(0.0542)
Regulatory capital	0.1511	0.1032	0.1604	0.1108
	(0.2670)	(0.2710)	(0.2746)	(0.2643)
Non-performing loans	-2.7428***	-2.8124***	-3.1334***	-2.7325***
	(0.4865)	(0.5004)	(0.6435)	(0.4674)
PR sets CCyB		-12.6473	-8.9488**	
		(10.1847)	(3.7879)	
CB sets CCyB		-6.8194		
		(9.2117)		
MF sets CCyB		-7.7255		
		(10.4509)		
FSC sets CCyB				9.5632
				(9.3317)
Observations	493	493	493	493
log-likelihood	-78.19	-77.51	-77.68	-77.70
χ^2 (DF)	113.26 (8)	132.43 (11)	74.75 (9)	134.60 (9)

Notes: The dependent variable is the binary CCyB decision. The models were estimated using a constant, which is not reported. Significance levels: *** 1%, ** 5%, * 10%. Data sources are provided in table 1.1.

the gap equals two percentage points, making this value a pivotal point. For this two percentage points value of the credit-to-GDP gap, we test if an increase in the gap leads to higher predicted probabilities of positive CCyBs. Additional indicators mentioned by the ESRB recommendation may be relevant for the calibration of the CCyB, which thus may also affect the probability of its implementation. Therefore, we test against different changes in the predicted probability. We perform χ^2-tests to test the null hypothesis that the conditional marginal effect of a one-unit increase in the credit-to-GDP gap on the predicted probability $\Pr(CCyB^{>0} = 1)$ equals 0, 25, 50, 75, or 100 percentage points, respectively. Table 1.6 reports conditional marginal effects (based on the estimation results of table 1.4) of a one-unit increase in the credit-to-GDP gap on the predicted probability $\Pr(CCyB^{>0} = 1)$ and the corresponding standard errors. The marginal effects are evaluated for the credit-to-GDP gap at two percentage points while all other variables are at their means. In line with our previous empirical results, these alternative hypotheses are rejected at conventional significance levels.

While our results indicate that the credit-to-GDP gap does not determine CCyB policies, this does not mean that the designated authorities decide in a discretionary way only. There are elements of “guidance” present in European CCyB policies. It seems that designated authorities use some of the indicators that have been proposed as more discretionary elements in a rather systematic, almost rule-based manner. Increases in house price growth, e.g., are significantly associated with higher log-odds ratios in the binary CCyB variable (specifications I-IV in table 1.4). Stronger house price inflation increases the probability that national designated authorities make use of the CCyB. Quantitatively, a one standard deviation increase in house price growth (versus its mean) raises the probability of using the buffer approximately by 6% - 8%, given all other covariates are at their means. This contrasts with Edge and Liang (2020) who do not find a significant relationship between positive CCyBs and house price changes. As they use annual data, their approach might not be able to pick up the dynamics of house price inflation and subsequent reactions of the regulators.

Also, an increase in distressed credit tends to lower the likelihood of the CCyB requirement, as indicated by a significant and negative coefficient for the non-performing loans as a percentage of total gross loans variable. The negative sign is consistent with the stabilizing objective of the CCyB, namely, to build up buffers under favorable economic conditions when the share of non-performing loans is low. The CCyB provides a pre-emptive cushion to be built up in good times when accumulating additional capital via retained earnings and raising capital is relatively easy (Couaillier et al., 2019). In bad times, the CCyB allows the release of capital to support banks in providing sufficient credit to the real economy, even when experiencing unexpected write-offs (ESRB, 2014). Given that non-performing loans are included as a contemporaneous variable, rising shares of non-performing loans signal that risks are already materializing to some extent, which implies a reduction of capital requirements as a countercyclical measure. Please note that the share of non-performing loans has been decreasing in almost all countries during the observation period. Interestingly, as with the credit-to-GDP gap, we do not find robust links to other systemic risk indicators mentioned before. This might reflect heterogeneous cross-sectional policy responses (e.g., ESRB (2019)) when taking additional risk indicators into account.

Institutional indicator variables that reflect which specific policy-maker is ultimately responsible for CCyB decisions are generally not significant. However, coefficients of the prudential regulator and the central bank are always negative. When controlling only for the Financial Stability Committee as the decision-making authority (FSC sets CCyB), the coefficient is positive, however, at an insignificant level. In contrast, the coefficient was significant in our robustness exercises. Overall, the results support the findings of Edge and Liang (2020). The probability of a positive CCyB is lower if the central bank or the prudential regulator decides. For the prudential regulator, the reduced likelihood to activate the countercyclical buffer may be explained by the focus - and possibly preference - on microprudential policy (Edge and Liang, 2020). Countries use the CCyB more likely if the FSC takes the final decision. FSCs that can set the CCyB directly are relatively powerful. Given their macroprudential focus, it is not surprising that they use the capital buffer more often.

So far, we have examined whether or not the countercyclical capital buffer is used, regardless of the specific setting of the rate. This aspect is in particular relevant for the decision of designated authorities to use the CCyB at all. In a second step, we analyze a complementary question, namely how decision-makers vary CCyB rates with respect to the macrofinancial environment by estimating the following linear unobserved effects model

$$CCyB_{it} = \alpha + \mathbf{x}'_{it}\boldsymbol{\beta} + u_i + v_t + \epsilon_{it}, \tag{1.3}$$

where $CCyB_{it}$ denotes the latest pending rate of the countercyclical capital buffer in country i for quarter t, α a constant, $\mathbf{x}_{it}$ the vector of aforementioned risk indicators for country i in quarter t, and $\boldsymbol{\beta}$ the corresponding parameters. u_i is the unobserved country effect, v_t the aggregate time effect, and ϵ_{it} the error term. We only include observations of countries that have already announced non-zero CCyB rates at at least one point in time through 2019.

Table 1.5 summarizes the results of the linear (fixed effects) regression with the announced buffer rate as the dependent variable. Again, as the insignificant coefficients of the credit-to-GDP gap (specifications I-III in table 1.5) indicate, there is no evidence that designated authorities base their CCyB decisions systematically on the officially recommended credit-to-GDP gap.

Analogous to the above discussion, we investigate in greater detail the potential role of the credit-to-GDP gap as the recommended rule-based element in CCyB policies. For the coefficients of the credit-to-GDP gap in table 1.5 we perform additional F-tests (reported in table 1.7). The coefficients are not tested against zero but against the linear slope parameter of the recommended buffer benchmark rule, H_0: $\beta_{Credit-to-GDP\ gap} = 0.3125$. The results of these tests imply that the alternative null hypotheses are clearly rejected on conventional significance levels, i.e., authorities do not set the CCyB according to the rule-based component (equation 1.1).

Table 1.5: Linear regression

CCyB	I	II	III
Credit-to-GDP gap	0.0107	0.0084	0.0021
	(0.0071)	(0.0058)	(0.0041)
Credit growth (1Y)	0.0156	0.0124	0.0088
	(0.0131)	(0.0133)	(0.0059)
House prices (5Y)	0.0290**	0.0190*	0.0092
	(0.0096)	(0.0099)	(0.0073)
Stock index (1Y)	-0.0029	-0.0044	0.0007
	(0.0029)	(0.0030)	(0.0035)
Stock index volatility	-0.0497	0.0182	0.0226
	(0.1614)	(0.0953)	(0.0521)
Current account	-0.0082	-0.0014	0.0001
	(0.0072)	(0.0031)	(0.0026)
Regulatory capital	0.0035	0.0500	0.0278
	(0.0654)	(0.0421)	(0.0211)
Non-performing loans	-0.0069	-0.1171**	-0.0337
	(0.0422)	(0.0423)	(0.0288)
Country FE	No	Yes	Yes
Year Effects	No	No	Yes
Observations	229	229	229
$R^2(within)$	0.42	0.52	0.72

Notes: The dependent variable is the announced CCyB level. All observations of countries were used which have announced positive CCyB rates at least once within the observation period. The models were estimated using a constant, which is not reported. Clustered standard errors (at country level) are reported in parentheses. Significance levels: *** 1%, ** 5%, * 10%. Data sources are provided in table 1.1.

Once again, house price growth seems to be policy-relevant, at least if we do not account for aggregate time effects (specification I-II). Thus, higher house price growth is not only associated with an increasing probability of setting a positive CCyB but also with higher rates, given the buffer is already activated. Quantitatively, an increase in house price inflation by 10 percentage points is associated with a rise in the buffer of approximately 0.2 - 0.3 percentage points. When we control for time effects, the sign remains robust while the coefficient becomes insignificant. This pattern may be caused by time trends, which are captured by the aggregate time effects in specification III.

When we control for both country fixed effects and aggregate time effects (specification III), all explanatory variables become insignificant. We will further elaborate on this finding in our robustness exercises.

In contrast to the binary response regression, improved credit quality, as measured by a decreased non-performing loans ratio, does not seem to result consistently in significantly higher buffer rates, given that the country has already implemented a CCyB policy. Country and time effects seem to play a crucial role when considering domestic non-performing loans ratios. This result might reflect that the standard deviation of non-performing loans within a given country is much lower than the standard deviation between different countries.

Taken together, our empirical results indicate that the policy to set a specific buffer rate should be distinguished from the general decision on using the CCyB at all. However, and not surprisingly, there exists considerable overlap. For both decisions, we do not find robust evidence that the credit-to-GDP gap is relevant - despite its prominent role in official communications. In contrast, in both decisions, house price inflation seems to play an important, systematic role. In the case of other risk indicators listed in the ESRB (2014) recommendation, policy-makers do not seem to focus on external imbalances or - interestingly - current regulatory bank capital. For the role of equity prices and their role in the buildup of risk, the timing might be crucial.[7]

[7] For instance, Borio and Lowe (2002a) found that equity price gaps peak earlier than other risk indicators.

Table 1.6: Additional χ^2-tests

$\Pr(CCyB^{>0} = 1)$	I		II		III		IV	
	dy/dx	SE	dy/dx	SE	dy/dx	SE	dy/dx	SE
Credit-to-GDP gap	0.0015	0.0041	0.0008	0.0026	0.0017	0.0049	0.0009	0.0027
$H_0 : dy/dx$ equals	χ^2 (1)	Prob>χ^2	χ^2 (1)	Prob>χ^2	χ^2 (1)	Prob>χ^2	χ^2 (1)	Prob>χ^2
0	0.13	0.7229	0.09	0.7583	0.12	0.7312	0.10	0.7538
0.25	3636.43	0.0000	8871.58	0.0000	2592.40	0.0000	8254.00	0.0000
0.5	14631.36	0.0000	35602.33	0.0000	10439.66	0.0000	33130.11	0.0000
0.75	32984.94	0.0000	80192.35	0.0000	23541.91	0.0000	74628.42	0.0000
1	58697.15	0.0000	$1.4 * 10^5$	0.0000	41899.15	0.0000	$1.3 * 10^5$	0.0000

Notes: The table reports conditional marginal effects dy/dx (based on the estimation results of table 1.4) of a one-unit increase in the credit-to-GDP gap on the predicted probability $\Pr(CCyB^{>0} = 1)$ and the corresponding standard errors (Delta-method). The marginal effects are evaluated for the credit-to-GDP gap at 2 pp while all other variables are at their means. The 2 pp threshold is used as the ESRB (2014) recommendation assigns positive buffer benchmark values for gaps exceeding 2 pp. The test statistics refer to the logistic regression results of table 1.4. The χ^2-test tests the null hypothesis that the conditional marginal effect dy/dx of a one-unit increase in the credit-to-GDP gap on the predicted probability $\Pr(CCyB^{>0} = 1)$ equals 0, 25, 50, 75, and 100 percentage points, respectively.

Table 1.7: Additional F-tests

Table	Coefficient	H_0	I		II		III	
			F Statistic	Prob >F	F Statistic	Prob >F	F Statistic	Prob >F
1.5	Credit-to-GDP gap	$\beta = 0.3125$	F(1,11)=1831.79	0.0000	F(1,11)=2722.99	0.0000	F(1,11)=5854.55	0.0000
1.10	Credit-to-GDP gap	$\beta = 0.3125$	F(1,11)=1083.30	0.0000	F(1,11)=1493.49	0.0000	F(1,11)=3748.66	0.0000
1.12	Credit-to-GDP gap	$\beta = 0.3125$	F(1,9)=1620.66	0.0000	F(1,9)=4042.28	0.0000	F(1,9)=4327.57	0.0000
1.14	Credit-to-GDP gap	$\beta = 0.3125$	F(1,11)=1850.34	0.0000	F(1,11)=3350.67	0.0000	F(1,11)=10463.67	0.0000
1.17	Credit-to-GDP gap	$\beta = 0.3125$	F(1,11)=2922.61	0.0000	F(1,11)=1113.29	0.0000	F(1,11)=5069.77	0.0000
1.17	Buffer guide	$\beta = 1$	F(1,11)=9.70	0.0098	F(1,11)=35.54	0.0001	F(1,11)=102.57	0.0000

Notes: The F-test tests the null hypothesis $\beta = 0.3125$ for the credit-to-GDP gap and $\beta = 1$ for the buffer guide, respectively.

1.5 Robustness

In the subsequent robustness analysis, we account for additional variables that signal the build-up of risk and discuss data availability issues as well as alternative estimation approaches.

National authorities are required to announce the credit-to-GDP ratio each quarter together with the credit-to-GDP gap (Art. 136, Directive 2013/36/EU (2013)). To account for diverging signals of alternative credit measures, we include the credit-to-GDP ratio[8] alongside the credit-to-GDP gap in the random-effects logit model and in the linear panel model. The ratio provides a debt measure standardized by the country's GDP.

As reported in table 1.9, the main findings in specifications (I)-(IV) do not alter. The coefficients of house price inflation are positive on the 1% significance level and have similar magnitudes. The negative effect of the contemporaneous share of non-performing loans is also robust against the additional consideration of the credit-to-GDP ratio. The institutional indicator variables have the expected sign, i.e., negative coefficients for the prudential regulator and the central bank and a positive coefficient for the FSC. In terms of the linear level regression (table 1.10), credit gaps remain insignificant. The coefficients of house price growth are qualitatively unaffected by the consideration of the additional variable. In accordance with our previous results (table 1.5), house price growth seems to be less critical when controlling both for country fixed effects and aggregate time effects.

Given the fundamental role of bank-based financing in Europe, decision-makers may focus more on bank credit than total non-financial debt. To assess if the specific measure of credit is crucial for our findings, we replace broad credit with bank credit (loans and debt securities granted by monetary financial institutions). As data is

[8]We retrieved credit-to-GDP ratios from the ESRB and national authorities. In most cases, we used the ratio based on the broad credit aggregate. However, for some countries, the ratio is available based on narrower aggregates only.

missing for some countries, the number of observations shrinks slightly. There are no material differences in the binary case (table 1.11) as house prices and non-performing loans seem to be the main drivers of CCyB policies. However, we do not see a clear pattern for adjustments over time (table 1.12), as the house price variable becomes insignificant when we control for the unobserved country- and time-effects.

While the credit-to-GDP ratio and gap data are those available at the time of decision (ESRB data set), we typically use contemporary observations that have not been publicly available at the time of decision in the case of the additional variables. Thus, we implicitly assume that decision-makers have a considerable information advantage for these variables. As a further problem, we only have ex-post revised time series that might differ from those available at the time of the decision. To account for potential information lags, we regress the CCyB on the first lags of the independent variables other than credit-to-GDP data, stock market variables, and the institutional indicators. Credit-to-GDP gaps and ratios from the ESRB data set were available at the time of the decision. Hence, we do not have to account for further information lags. Similarly, we do not use lagged values of the stock-market data as stock index data is available in real-time. We notice differences for the CCyB indicator regression (table 1.13) as we identify more significant coefficients. While the influence of house price inflation and non-performing loans does not change qualitatively, the credit-to-GDP gap and stock price changes become important. Consistent with intuition and the ESRB (2014) recommendation, higher credit gaps are associated with a higher likelihood to use the capital buffer. The negative sign of the year-on-year change of stock prices is against intuition, which states that higher equity valuations may indicate a build-up of systemic risk. Interestingly, we also identify more significant coefficients for the linear level regression. Credit growth and house price inflation are relevant when we control for the unobserved country and aggregate time effects (table 1.14, specification III). The coefficient of the credit-to-GDP gap is insignificant in all of the three specifications.

Analogous to the approach of Edge and Liang (2020), we check if the selection of the specific logit-models is crucial for our outcomes. Amemiya (1981) argues that probit and logit models lead to similar results as long as the data is not strongly concentrated at the end of the probability distribution. This concentration could be an issue since many non-positive CCyBs imply a high distribution mass at zero. Amemiya (1981) shows, that logit coefficients can be approximately converted into probit estimates by applying the formula $\hat{\beta}_L = 1.6\hat{\beta}_P$, where $\hat{\beta}_L$ denotes the logit coefficient and $\hat{\beta}_P$ the probit estimate. Again, the credit-to-GDP gap is insignificant in the probit estimation (table 1.15). In contrast, house prices remain significant. The probit estimates show stronger evidence for the negative (positive) impact on the likelihood of setting positive CCyBs when the prudential regulator (the financial stability committee) decides.

As the independent variables measure systemic risk in different dimensions, it should be informative to inspect the co-movements of the explanatory variables when interpreting multivariate regression results.[9] Coefficients of correlation are reported for the continuous explanatory variables (table 1.3). None of the bivariate correlations exceeds 0.6. In our baseline regressions (table 1.4 and table 1.5) in which we do not include the MFI credit growth, the highest bivariate correlation is below 0.5. We also calculated the centered variance inflation factors (VIF) for all continuous variables included in the linear level regression without unobserved effects (column I in the linear regression, table 1.5). The resulting VIFs (not reported) are small and, as indicated by the bivariate correlation measures, do not show a severe multicollinearity problem.

We also performed univariate analyses by regressing the CCyB level and the binary CCyB indicator variable on all continuous variables separately.

Intuitively, if the "rules-based approach" was the main driver for CCyB decisions, we would expect a strong positive and significant relationship between the buffer

[9]We thank an anonymous referee for pointing out this aspect.

guide and the CCyB. It may be helpful here to think of an "ideal world" in which the credit-to-GDP gap - and hence the buffer benchmark - is a measure accepted by all national designated authorities that properly reflects the risks in the financial sector. We, therefore, regressed CCyB decisions on the buffer guide (derived from the credit-to-GDP gap), which we took from the ESRB data set. For the linear case, the slope parameter should be approximately equal to one. As shown in table 1.16 and table 1.17, the buffer guide was neither significantly different from zero for the CCyB indicator variable nor the buffer level. Consistent with our previous regressions, we considered only countries that have used the macroprudential instrument at least once within the observation period in the latter case. The null hypothesis that the linear coefficient of the credit-to-GDP gap equals 0.3125, and for the buffer guide one respectively, is clearly rejected on conventional levels (table 1.7). The univariate results in table 1.16 support the positive impact of house price inflation and the negative influence of non-performing loans on the likelihood of using the buffer. Both variables also seem relevant for buffer calibration (table 1.17), at least when we do not control for the country- and time-effects. In univariate approaches, the stock market variables seem to be more relevant.

1.6 Conclusions

Based on its "guided discretion" approach, the European Systemic Risk Board recommends a prominent role of the credit-to-GDP gap and the related benchmark buffer rate. However, our empirical analysis indicates that the credit-to-GDP gap, as the rule-based element, seems to be only of a minor, if any, relevance for national macroprudential policies.

Interestingly, that does not mean that national authorities act in a downright discretionary way only. We find that policy-makers systematically take into account some of the other risk indicators related to the financial cycle as suggested by the

ESRB (2014). In particular, they seem to react to house price inflation when setting the countercyclical buffer rate for domestic exposure. This is likely to reflect concerns about potential overvaluations in real estate markets, the subsequent risk of bursting housing bubbles, and distress in the banking sector. As pointed out by Borio and Lowe (2002b) and Borio (2014) among others, real estate prices are a key driver of the financial cycle. Also, credit quality, as measured by the non-performing loans ratio, appears to play an important role in setting the countercyclical capital buffer.

Our empirical results are related to a conflict that has been discussed at great length in the field of monetary policy. In choosing their policy framework, policy-makers do not only have the choice between (pure) rules versus (pure) discretion. Rather, discretion can be constrained by implementing *rule-like* features (Mishkin, 2017). A similar logic might hold in the field of macroprudential policy. By strengthening rule-like elements in their policy decisions, authorities could possibly improve the efficiency of their policies. Rule-based components enhance the comparability of macroprudential policy among different countries and should make decisions more comprehensible to financial markets. Transparent communication of indicators and their consistent application could improve the predictability of capital buffer decisions and reduce adaption costs for financial institutions.

Unsurprisingly, some caveats should be kept in mind. Since the CCyB is a relatively novel instrument, our analysis does not cover policy decisions for the entire financial cycle. Moreover, the reporting of consistent data (e.g., credit-to-GDP gaps, credit-to-GDP ratios) on the European level is still in its infancy. Consistently calculated and published indicators would help to improve the analysis of European CCyB decisions.

Finally, it is puzzling that national authorities do not stick more closely to the buffer guide rule they have agreed to as ESRB members. Apparently, they are not at odds with a systematic CCyB policy, at least when it is based on indicators such as house price inflation and credit quality. By not following the officially agreed-upon credit-to-GDP rule while concentrating on complementary variables, they pursue rather non-transparent and inconsistent policies. They neglect the potentially relevant information channel of their policies and forego the benefits of a time-consistent policy. In this situation, the following two options seem available. Either the ESRB recommendations are brought in line with the current CCyB policies on the national level, or else national buffer decisions should be more closely linked to the single quantitative rule.

1.7 Appendix

Table 1.8: Countries and domestic CCyB rates

Country	Code	Decision date	CCyB (Pending rate)
Austria	AT	2019-09-05	0.00
Belgium	BE	2019-09-16	0.50
Bulgaria	BG	2019-09-17	1.00
Croatia	HR	2019-09-30	0.00
Cyprus	CY	2019-09-10	0.00
Czech Republic	CZ	2019-08-29	2.00
Denmark	DK	2019-10-01	2.00
Estonia	EE	2019-09-30	0.00
Finland	FI	2020-09-27	0.00
France	FR	2019-07-09	0.50
Germany	DE	2019-09-30	0.25
Greece	GR	2019-09-16	0.00
Hungary	HU	2019-09-24	0.00
Iceland	IS	2019-10-01	2.00
Ireland	IE	2019-07-04	1.00
Italy	IT	2019-09-17	0.00
Latvia	LV	2019-10-29	0.00
Lithuania	LT	2019-09-27	1.00
Luxembourg	LU	2019-10-01	0.25
Malta	MT	2019-10-01	0.00
Netherlands	NL	2019-09-24	0.00
Norway	NO	2019-09-19	2.50
Poland	PL	2019-09-23	0.00
Portugal	PT	2019-10-01	0.00
Romania	RO	2019-09-11	0.00
Slovakia	SK	2019-10-21	2.00
Slovenia	SI	2019-11-05	0.00
Spain	ES	2019-09-20	0.00
Sweden	SE	2019-10-24	2.50
United Kingdom	UK	2019-10-02	1.00

Source: ESRB. Latest available data as per December 2019.

Table 1.9: Random-effects logistic regression (robustness - including credit-to-GDP ratio)

$CCyB^{>0}$	I	II	III	IV
Credit-to-GDP gap	0.0724	0.0966	0.0908	0.0782
	(0.0594)	(0.0594)	(0.0607)	(0.0580)
Credit growth (1Y)	-0.2293	-0.2235	-0.2354	-0.2206
	(0.1531)	(0.1532)	(0.1541)	(0.1512)
Credit-to-GDP ratio	0.0237	0.0161	0.0267	0.0120
	(0.0248)	(0.0256)	(0.0251)	(0.0230)
House prices (5Y)	0.3406***	0.3513***	0.3395***	0.3427***
	(0.0482)	(0.0465)	(0.0447)	(0.0448)
Stock index (1Y)	-0.0460	-0.0453	-0.0469	-0.0462
	(0.0353)	(0.0350)	(0.0358)	(0.0346)
Stock index volatility	0.9340	1.1609	1.0572	0.9966
	(1.2959)	(1.3077)	(1.3102)	(1.2788)
Current account	0.0050	0.0069	0.0060	0.0037
	(0.0565)	(0.0572)	(0.0578)	(0.0549)
Regulatory capital	0.1278	0.0717	0.1818	0.1018
	(0.2723)	(0.2676)	(0.2709)	(0.2640)
Non-performing loans	-2.8586***	-2.8453***	-2.9178***	-2.7471***
	(0.5067)	(0.5189)	(0.5366)	(0.4772)
PR sets CCyB		-13.2799	-7.9125**	
		(9.6087)	(3.8240)	
CB sets CCyB		-5.3819		
		(9.3447)		
MF sets CCyB		-7.1296		
		(10.7378)		
FSC sets CCyB				8.9232*
				(4.7253)
Observations	493	493	493	493
log-likelihood	-77.82	-77.36	-77.38	-77.61
χ^2 (DF)	109.34 (9)	132.43 (12)	115.13 (10)	140.84 (10)

Notes: The dependent variable is the binary CCyB decision. The models were estimated using a constant, which is not reported. Significance levels: *** 1%, ** 5%, * 10%. Data sources are provided in table 1.1.

Table 1.10: Linear regression (robustness - including credit-to-GDP ratio)

CCyB	I	II	III
Credit-to-GDP gap	0.0134	0.0042	0.0030
	(0.0091)	(0.0080)	(0.0051)
Credit growth (1Y)	0.0188	0.0141	0.0083
	(0.0119)	(0.0133)	(0.0060)
Credit-to-GDP ratio	0.0019	0.0056	-0.0012
	(0.0024)	(0.0058)	(0.0033)
House prices (5Y)	0.0298**	0.0173*	0.0094
	(0.0104)	(0.0092)	(0.0073)
Stock index (1Y)	-0.0039*	-0.0044	0.0007
	(0.0020)	(0.0027)	(0.0036)
Stock index volatility	-0.1251	0.0510	0.0167
	(0.1761)	(0.0799)	(0.0567)
Current account	-0.0086	-0.0008	-0.0000
	(0.0070)	(0.0030)	(0.0026)
Regulatory capital	-0.0080	0.0528	0.0268
	(0.0649)	(0.0425)	(0.0214)
Non-performing loans	-0.0020	-0.1304***	-0.0294
	(0.0511)	(0.0417)	(0.0293)
Country FE	No	Yes	Yes
Year Effects	No	No	Yes
Observations	229	229	229
$R^2(within)$	0.43	0.53	0.72

Notes: The dependent variable is the announced CCyB level. All observations of countries were used which have announced positive CCyB rates at least once within the observation period. The models were estimated using a constant, which is not reported. Clustered standard errors (at country level) are reported in parentheses. Significance levels: *** 1%, ** 5%, * 10%. Data sources are provided in table 1.1.

Table 1.11: Random-effects logistic regression (robustness - MFI credit growth)

$CCyB^{>0}$	I	II	III
Credit-to-GDP gap	0.0130	0.0064	0.0045
	(0.0658)	(0.0697)	(0.0756)
MFI credit growth (1Y)	0.2463	0.1974	0.1977
	(0.1912)	(0.1920)	(0.2374)
House prices (5Y)	0.3918***	0.3753***	0.4209***
	(0.0466)	(0.0495)	(0.0855)
Stock index (1Y)	-0.0154	-0.0156	-0.0140
	(0.0366)	(0.0355)	(0.0392)
Stock index volatility	2.4010	2.1623	2.5014
	(1.6737)	(1.6434)	(1.8624)
Current account	-0.0078	-0.0051	-0.0036
	(0.0522)	(0.0525)	(0.0557)
Regulatory capital	-0.0928	-0.1261	0.0260
	(0.3043)	(0.2943)	(0.3362)
Non-performing loans	-2.5832***	-2.5446***	-2.8701***
	(0.4465)	(0.4813)	(0.5586)
PR sets CCyB		-1.0146	-3.2881
		(6.4524)	(4.3199)
CB sets CCyB		-1.3422	
		(5.4938)	
Observations	454	454	454
log-likelihood	-60.20	-60.50	-60.29
χ^2 (DF)	149.83	119.68	51.86

Notes: The dependent variable is the binary CCyB decision. The models were estimated using a constant, which is not reported. Significance levels: *** 1%, ** 5%, * 10%. Data sources are provided in table 1.1.

Table 1.12: Linear regression (robustness - MFI credit growth)

CCyB	I	II	III
Credit-to-GDP gap	0.0123	0.0058	0.0038
	(0.0075)	(0.0048)	(0.0047)
MFI credit growth (1Y)	-0.0303	-0.0390	-0.0177
	(0.0378)	(0.0214)	(0.0209)
House prices (5Y)	0.0304**	0.0207*	0.0090
	(0.0119)	(0.0097)	(0.0074)
Stock index (1Y)	-0.0008	-0.0020	0.0022
	(0.0030)	(0.0032)	(0.0038)
Stock index volatility	-0.0826	0.0263	0.0249
	(0.1837)	(0.1039)	(0.0627)
Current account	-0.0117	-0.0023	-0.0000
	(0.0067)	(0.0028)	(0.0024)
Regulatory capital	-0.0159	0.0265	0.0340
	(0.0693)	(0.0431)	(0.0310)
Non-performing loans	-0.0194	-0.1334**	-0.0631*
	(0.0515)	(0.0443)	(0.0294)
Country FE	No	Yes	Yes
Year Effects	No	No	Yes
Observations	190	190	190
$R^2(within)$	0.42	0.56	0.73

Notes: The dependent variable is the announced CCyB level. All observations of countries were used which have announced positive CCyB rates at least once within the observation period. The models were estimated using a constant, which is not reported. Clustered standard errors (at country level) are reported in parentheses. Significance levels: *** 1%, ** 5%, * 10%. Data sources are provided in table 1.1.

Table 1.13: Random-effects logistic regression (lags)

$CCyB^{>0}$	I	II	III	IV
Credit-to-GDP gap	0.1029	0.1061*	0.1158*	0.0872**
	(0.0672)	(0.0627)	(0.0644)	(0.0391)
Credit growth (1Y, L1)	-0.2171	-0.2300	-0.2343	-0.1327
	(0.1510)	(0.1475)	(0.1525)	(0.1066)
House prices (5Y, L1)	0.3802***	0.3530***	0.3738***	0.2471***
	(0.0506)	(0.0453)	(0.0464)	(0.0322)
Stock index (1Y)	-0.0962***	-0.0963***	-0.0983***	-0.0786***
	(0.0364)	(0.0354)	(0.0362)	(0.0249)
Stock index volatility	-1.1079	-1.0599	-1.1061	-0.9390
	(0.8720)	(0.8684)	(0.8750)	(0.7498)
Current account (L1)	0.0009	0.0083	0.0079	-0.0080
	(0.0545)	(0.0548)	(0.0564)	(0.0418)
Regulatory capital (L1)	0.3469	0.4245*	0.4099*	0.2001
	(0.2553)	(0.2257)	(0.2351)	(0.1609)
Non-performing loans (L1)	-2.6573***	-2.6122***	-2.7503***	-1.6300***
	(0.4876)	(0.4673)	(0.4805)	(0.2616)
PR sets CCyB		-14.7971	-8.8388**	
		(9.6831)	(4.0135)	
CB sets CCyB		-7.3223		
		(9.0534)		
MF sets CCyB		-7.4182		
		(10.3989)		
FSC sets CCyB				3.4595*
				(1.8554)
Observations	512	512	512	512
log-likelihood	-78.62	-77.71	-77.84	-83.10
χ^2 (DF)	144.46 (8)	155.61 (11)	156.01 (9)	257.47 (9)

Notes: The dependent variable is the binary CCyB decision. The models were estimated using a constant, which is not reported. Significance levels: *** 1%, ** 5%, * 10%. Data sources are provided in table 1.1.

Table 1.14: Linear regression (lags)

CCyB	I	II	III
Credit-to-GDP gap	0.0125	0.0076	0.0042
	(0.0070)	(0.0053)	(0.0030)
Credit growth (1Y, L1)	0.0141	0.0182*	0.0128**
	(0.0115)	(0.0096)	(0.0053)
House prices (5Y, L1)	0.0315***	0.0227**	0.0174**
	(0.0089)	(0.0083)	(0.0071)
Stock index (1Y)	-0.0026	-0.0054*	0.0005
	(0.0027)	(0.0029)	(0.0036)
Stock index volatility	-0.0980	-0.1438	-0.0271
	(0.1353)	(0.0893)	(0.0578)
Current account (L1)	-0.0062	-0.0003	-0.0007
	(0.0080)	(0.0018)	(0.0027)
Regulatory capital (L1)	-0.0041	0.0403	0.0286
	(0.0636)	(0.0334)	(0.0227)
Non-performing loans (L1)	0.0112	-0.0740*	-0.0250
	(0.0413)	(0.0410)	(0.0336)
Country FE	No	Yes	Yes
Year Effects	No	No	Yes
Observations	236	236	236
$R^2(within)$	0.45	0.55	0.69

Notes: The dependent variable is the announced CCyB level. All observations of countries were used which have announced positive CCyB rates at least once within the observation period. The models were estimated using a constant, which is not reported. Clustered standard errors (at country level) are reported in parentheses. Significance levels: *** 1%, ** 5%, * 10%. Data sources are provided in table 1.1.

Table 1.15: Random-effects probit regression

$CCyB^{>0}$	I	II	III	IV
Credit-to-GDP gap	0.0393	0.0495	0.0446	0.0507
	(0.0336)	(0.0340)	(0.0342)	(0.0368)
Credit growth (1Y)	-0.1222	-0.0928	-0.1171	-0.1368
	(0.0842)	(0.0735)	(0.0817)	(0.0921)
House prices (5Y)	0.2136***	0.1762***	0.2011***	0.2294***
	(0.0277)	(0.0214)	(0.0331)	(0.0313)
Stock index (1Y)	-0.0258	-0.0256	-0.0267	-0.0231
	(0.0200)	(0.0177)	(0.0197)	(0.0206)
Stock index volatility	0.6389	0.4689	0.6550	0.8075
	(0.7372)	(0.6626)	(0.7367)	(0.7723)
Current account	-0.0040	-0.0068	-0.0029	-0.0015
	(0.0302)	(0.0265)	(0.0293)	(0.0317)
Regulatory capital	0.1189	0.1415	0.1537	0.1220
	(0.1537)	(0.1423)	(0.1575)	(0.1509)
Non-performing loans	-1.5564***	-1.2757***	-1.4997***	-1.7006***
	(0.2190)	(0.1808)	(0.2000)	(0.2960)
PR sets CCyB		-5.5355***	-4.1937*	
		(1.4388)	(2.1658)	
CB sets CCyB		-2.9510*		
		(1.6157)		
MF sets CCyB		-2.2030		
		(2.6578)		
FSC sets CCyB				5.2927***
				(2.0268)
Observations	493	493	493	493
log-likelihood	-78.09	-77.41	-77.92	-77.12
χ^2 (DF)	124.48 (8)	169.89 (11)	109.06 (9)	82.31 (9)

Notes: The dependent variable is the binary CCyB decision. The models were estimated using a constant, which is not reported. Significance levels: *** 1%, ** 5%, * 10%. Data sources are provided in table 1.1.

Table 1.16: Binary regression - univariate

Dependent variable	Independent variable	Coefficient
$CCyB^{>0}$	Buffer guide	-0.3611 (0.5373)
$CCyB^{>0}$	Credit-to-GDP gap	-0.0105 (0.0194)
$CCyB^{>0}$	Credit growth (1Y)	0.0306 (0.0354)
$CCyB^{>0}$	House prices (5Y)	0.2622*** (0.0510)
$CCyB^{>0}$	Stock index (1Y)	-0.0468*** (0.0130)
$CCyB^{>0}$	Stock index volatility	-1.0410** (0.5128)
$CCyB^{>0}$	Current account	0.0050 (0.0220)
$CCyB^{>0}$	Regulatory capital	0.1262 (0.1062)
$CCyB^{>0}$	Non-performing loans	-4.4152*** (0.8738)
Observations		493

Notes: The dependent variable is the binary CCyB decision. The models were estimated using a constant, which is not reported. Significance levels: *** 1%, ** 5%, * 10%. Data sources are provided in table 1.1.

Table 1.17: Linear regression - univariate

Dependent variable	Independent variable	I	II	III
CCyB	Buffer guide	0.1669	-0.3945	-0.1702
		(0.2675)	(0.2339)	(0.1155)
CCyB	Credit-to-GDP gap	0.0055	-0.0090	-0.0021
		(0.0057)	(0.0096)	(0.0044)
CCyB	Credit growth (1Y)	0.0231	0.0068	0.0066
		(0.0194)	(0.0098)	(0.0041)
CCyB	House prices (5Y)	0.0243**	0.0296***	0.0098
		(0.0106)	(0.0084)	(0.0071)
CCyB	Stock index (1Y)	-0.0057	-0.0079	0.0003
		(0.0035)	(0.0049)	(0.0038)
CCyB	Stock index volatility	-0.1354	-0.3853**	-0.0460
		(0.1487)	(0.1382)	(0.0485)
CCyB	Current account	-0.0010	0.0006	0.0010
		(0.0075)	(0.0034)	(0.0024)
CCyB	Regulatory capital	0.0502	0.0515	0.0168
		(0.0665)	(0.0670)	(0.0172)
CCyB	Non-performing loans	-0.0651*	-0.1851***	-0.0421*
		(0.0351)	(0.0566)	(0.0213)
Country FE		No	Yes	Yes
Year Effects		No	No	Yes
Observations		229	229	229

Notes: The dependent variable is the announced CCyB level. All observations of countries were used which have announced positive CCyB rates at least once within the observation period. The models were estimated using a constant, which is not reported. Clustered standard errors (at country level) are reported in parentheses. Significance levels: *** 1%, ** 5%, * 10%. Data sources are provided in table 1.1.

Chapter 2

ECB Monetary Policy Announcements and Bank Stock Returns

Abstract

Long-term profitability of banks is relevant for their capital structure and financial stability considerations. Using market valuation as a measure for profitability, we investigate the influence of ECB announcements on stock prices of European banks from 2000 to 2021. Building on Jarociński and Karadi (2020), we identify pure monetary and information shocks based on high-frequency movements in interest rates and the European stock market. After the financial crisis, bank stocks are significantly more sensitive to information shocks than stocks in general. We present evidence that the relationship between shocks transmitted by ECB announcements and bank stock returns changes substantially over time. Cross-sectional heterogeneity of sensitivities is related to bank characteristics such as size or the financing structure.

2.1 Motivation

The period of very low interest rates and discussions about the timing and pace of a monetary tightening in the EA raised questions about asset price reactions to central bank decisions. Relevant literature finds an inverse relationship between stock markets and surprises in interest rates induced by central bank announcements (Bernanke and Kuttner, 2005; Gürkaynak et al., 2005). Lower interest rates are expected to reduce the cost of financing and increase future expected cash flows. Positive stock price reactions to expansionary monetary policy announcements can also be driven by lower discount factors, i.e., higher present values of future expected cash flows (e.g., Thorbecke (1997)). Theoretically, both effects increase stock valuations. Empirical evidence on the relationship between monetary policy and equity indices, which typically underpin this view, is well established.

However, there are good reasons why monetary policy may influence the price of bank stocks differently. While the second channel, i.e., higher equity prices through lower discount rates, also applies to banks, it is unlikely that lower interest rates increase per se expected future cash flows for banks, especially from their interest incomes. That banks might benefit instead from higher interest rates has been discussed for a long time, e.g., in a widely noticed work Samuelson (1945, p. 16) formulated the proposition

> "The banking system as a whole is not really hurt by an increase in the whole complex of interest rates. It is left tremendously better off by such a change."

Even though the empirical findings on the interrelation of interest rates and bank profitability are mixed, there is a consensus that an extended period of low interest rates adversely affects bank profitability (e.g., Altavilla et al., 2018; Borio et al., 2017). The difference between the short- and long-term rates can be a crucial driver since in the traditional (maturity transformation) business model of banks, there is typically long-term lending and short-term borrowing (English et al., 2018, p. 81).

An ongoing weakness in bank profitability is a major threat to financial stability. It should be kept in mind that interest rate hikes in a low interest rate environment may entail a beneficial impact on banks' profitability and, thus, indirectly on financial stability (Altavilla et al., 2018). Obviously, low profitability impedes the ability to finance equity capital internally, which serves as a cushion when losses materialize during economic downturns. Hence, the question of to which extent the ECB's monetary policy is responsible for the level of profitability of European banks is highly relevant from a supervisory perspective.

Assuming that the stock market is sufficiently efficient, returns can reveal the change in investors' attitudes towards the future earnings of banks with respect to monetary policy decisions. This has consequences for the equity-financing of banks and also for financial stability. Using high-frequency data on bank stock prices, we analyze (i) if bank stocks react systematically differently to shocks transmitted by monetary policy announcements than the overall stock market, (ii) if bank stocks immediately react to surprises in the slope of the yield curve and if (iii) the relationship changes over time. Moreover, we will study the role of potential drivers for heterogeneous reactions. To account for possible information effects in ECB communication, we follow Jarociński and Karadi (2020) in decomposing interest rate surprises during ECB announcements into a (pure) monetary policy and a central bank information shock. The idea behind the information shock is that a policy tightening may result in higher stock prices since the market associates the policy change with improved future conditions which is good news for stock markets. While information effects lead to same-sign changes in stock prices and market interest rates, a positive monetary policy shock causes inverse reactions in stock markets and interest rates (Jarociński and Karadi, 2020).

We find that after the financial crisis bank stocks have shown specific responses as they have reacted more sensitively to information shocks transmitted by ECB communication. Moreover, positive surprises in the slope of the yield curve have, in contrast to the general stock market, positive effects on bank stocks. These effects are time-dependent, which might be driven by the state of the monetary environment. Studying potential drivers of cross-sectional heterogeneity, we find that stocks of banks that are larger, have a lower deposit ratio, or are located in a fixed-rate country show on average higher sensitivities to ECB shocks. However, the results on heterogeneity should not be interpreted causally.

The remainder is organized as follows. Section 2.2 reviews the existing literature on monetary policy, bank profitability, and stock returns. Section 2.3 presents the data and explains the identification used for our empirical analysis. In section 2.4, we describe the empirical procedure, explain the results, and discuss them in light of the existing literature. Section 2.5 investigates potential reasons for the heterogeneity of stock price reactions. Finally, section 2.6 concludes.

2.2 Literature

2.2.1 Monetary Policy and Stock Prices

2.2.1.1 Monetary Policy Announcements and Stock Indices

Empirical studies support the view that easing monetary policy boosts stock markets. Thorbecke (1997) estimates the effect of US monetary policy on stock returns of industry portfolios. Using distinct monetary policy proxies and several empirical approaches such as vector autoregression (VAR), a narrative monetary policy index, event study methodology, and a multifactor model, he consistently estimates that expansionary monetary interventions have a positive effect on stock returns (Thorbecke, 1997).

A large number of studies explore the transmission of monetary policy actions to market interest rates. In pivotal work, Cook and Hahn (1989) study the reaction of market interest rates to Federal Reserve target rate changes in the 1970s. They find substantial, moderate, and small movements in short-term, medium-term, and, long-term market interest rates, respectively. The slope of the yield curve up to 12 months is insensitive to target rate changes as short-term market interest rates (i.e., treasury bill rates of 3 months, 6 months, and, 12 months maturity) react similarly (Cook and Hahn, 1989). Kuttner (2001) uses US Federal funds futures to disentangle expected and unexpected changes in the target interest rates. Market interest rates react only very slightly to expected changes, while there are large market reactions to unanticipated changes (Kuttner, 2001). Gürkaynak et al. (2007) argue in favor of market-based measures to proxy near-term monetary policy expectations, in particular, for the measurement of monetary policy shocks around FOMC meetings. For horizons up to six months, the federal funds futures outperform other financial instruments (e.g., term federal funds, Eurodollar deposits, commercial paper) in predicting the federal funds rate (Gürkaynak et al., 2007).

Thornton (2014) highlights some problems of monetary policy measures calculated from market-based indicators. If market-based proxies for monetary policy shocks also react to other (non-monetary) news, the estimated response of asset prices will be biased (i.e., the "joint-response-bias"). Not considering this bias may result in overestimating reactions of asset prices (Thornton, 2014).

Bernanke and Kuttner (2005) estimate the effect of US Federal Reserve monetary policy shocks on the broad stock market and industry-specific portfolios, distinguishing between unanticipated and anticipated actions of the central bank. They find that an unexpected rate reduction of 25 basis points leads on average to a positive 1% increase in the broad stock market. However, monetary policy shocks can only explain a relatively small share of the stock market variation (Bernanke and Kuttner, 2005). Gürkaynak et al. (2005) identify a similar effect in size, as a 25 basis points tightening is associated with a circa 1% decrease in the S&P 500. Unlike Bernanke and Kuttner (2005), they use intraday data and measure changes in asset prices within event-windows surrounding monetary events. Moreover, Gürkaynak et al. (2005) find that two factors (i.e., target factor and path factor) are required to describe the effects of FOMC policy decisions on asset prices as monetary policy statements convey information beyond the current target rate. The two factors reflect surprises in the contemporary rate target, and the independent changes in the future rate respectively (Gürkaynak et al., 2005). Gürkaynak (2005) extracts level, timing, and slope surprises from federal funds futures and subsequently regresses asset price reactions on these three factors. Applying the methodologies proposed in Gürkaynak et al. (2005) and Gürkaynak (2005) to the EA, Jardet and Monks (2014) decompose factors related to different horizons from high-frequency changes in Overnight Index Swap (OIS) rates.[1] They provide evidence that expansionary surprises during the announcement of monetary decisions (press release) increase stock prices in the EA (Jardet and Monks, 2014).

The inverse relationship between interest rates and stock returns shows up in different regions, as Rogers et al. (2014, p. 769) find a positive impact of expansionary monetary policy shocks on stock markets in the US, the UK, and the EA. In their analysis, Rogers et al. (2014) regress asset price changes on monetary surprise variables constructed from changes in market-based indicators.

The publication process of ECB announcements, which is divided into the decision (press release) and the press conference (introductory statement and Q&A), can provide new insights into the transmission of monetary policy impulses using intraday data. For ECB announcements, Ehrmann and Fratzscher (2009) have shown that the press conference can have stronger effects on financial markets than the actual monetary policy decision.

Other studies focusing more on volatility shed further light on the behavior of stock markets during monetary policy news, such as Andersson (2010) or the

[1]For further details on OIS rates and their usage as an indicator for expectations about future monetary policy, see Lloyd (2018).

GARCH-applications of Bomfim (2003) and Farka (2009). Hussain (2011) highlights, consistent with Farka (2009), that the use of (high-frequency) intraday data is crucial to reduce endogeneity issues and the omitted variable bias. In line with Ehrmann and Fratzscher (2009), Hussain (2011) shows that ECB press conferences have a significant impact on financial markets in Europe.

In a recent work on the EA, Altavilla et al. (2019) extract ECB monetary policy surprise factors from intraday changes in OIS rates. The authors make use of the ECB's news disclosure process and distinguish between the press release and the press conference window. In a second step, Altavilla et al. (2019) regress asset price reactions within these event windows on policy surprise factors and find that monetary tightening surprises are associated with drops in the general stock market and the banking sub-index. A number of current studies separate distinct shocks transmitted by central bank announcements (Jarociński and Karadi, 2020; Cieslak and Schrimpf, 2019; Andrade and Ferroni, 2021; Miranda-Agrippino and Ricco, 2021). The underlying idea is that central bank communications may contain information about future economic developments in addition to purely monetary news. These studies use high-frequency data in time windows around monetary policy announcements to infer shocks from price changes in financial instruments.

Cieslak and Schrimpf (2019) derive monetary policy shocks and non-monetary, i.e., growth and risk premium, shocks from the co-movement of stocks and yields of different maturities. They show that non-monetary shocks occur in particular in communications accompanying the monetary decision, such as press conferences, and that they play an essential role in asset price reactions during the financial crisis (Cieslak and Schrimpf, 2019).

In a related study, Jarociński and Karadi (2020) are using a structural VAR and exploit the relationship of stock prices and market interest rates to disentangle pure monetary policy and central bank information shocks. While a positive monetary policy shock, i.e., monetary tightening, increases market interest rates and drives stock markets down, central bank information shocks move market interest rates and equities in the same direction. Accounting for these distinct shocks is particularly important in the EA, since stock market movements and interest rates surprises have the same sign for almost half of the announcements (Jarociński and Karadi, 2020, p. 3). Jarociński (2020) studies the role of monetary policy and central bank information shocks for transatlantic spillovers of central bank announcements. Persistent spillovers from the EA exist only when interest rates and stock markets in Europe move together, i.e., when the central bank information shock in ECB communication dominates. In these cases, the response of US markets is similar to shocks when European economic news is released (Jarociński, 2020).

Andrade and Ferroni (2021) point out that it is crucial to differentiate between monetary policy surprises conveying news on future economic conditions and news about future monetary policy interventions. To do so, they decompose the path-factor into a "Delphic" and "Odyssean" component based on the co-movement of yields and market-based inflation expectations.[2] While "Odyssean" shocks, e.g., tighter future monetary policy given the economic outlook, lead to a negative stock market reaction, the reverse holds for "Delphic" shocks (e.g., improved macroeconomic outlook) (Andrade and Ferroni, 2021).

Miranda-Agrippino and Ricco (2021) reach similar conclusions by showing that pure monetary shocks are mixed up with information shocks in standard measures of monetary policy interventions. This can lead to puzzling findings regarding the relationship between interest rates, economic activity, prices, and equity markets. They find that a pure monetary tightening is unambiguously associated with a decline in economic activity and a drop in stock prices (Miranda-Agrippino and Ricco, 2021).

[2] The terminology "Odyssean" and "Delphic" roots back to Campbell et al. (2012). While a public commitment about future monetary policy actions is "Odyssean" forward guidance, "Delphic" forward guidance may consist of central bank forecasts about the economy and the expected stance of the policy.

2.2.1.2 Monetary Policy Announcements and Banks Stocks

Various studies analyze the general effect of interest rates on stock prices, with and without a specific focus on monetary policy announcements. While findings in earlier studies indicate that higher (short- and/or long-term) rates have an adverse effect on the return of bank equities (Flannery and James, 1984; Elyasiani and Mansur, 1998, 2004), recent studies draw different conclusions by finding mixed or positive reactions (Elyasiani et al., 2020; Foos et al., 2022).

Focusing on monetary policy, Madura and Schnusenberg (2000) study the effects of Fed policy announcements on US bank stock returns from 1974 to 1996. They find an inverse relationship between interest rates and bank stock returns. While interest rate reductions lead to higher equity returns, there is less evidence that bank stock returns decrease due to monetary tightening (Madura and Schnusenberg, 2000).

In their event study analysis based on daily data, Yin et al. (2010) investigate the impact of changes in the federal funds target rate on the returns of bank equity. In line with previous studies, they find that stock returns are inversely related to unexpected innovations in the target rate and the reaction reveals state-dependencies (Yin et al., 2010).

Transferring these findings directly to the current monetary policy environment is questionable, as some studies suggest stronger effects of unconventional policies on stock prices compared to standard interest rate decisions (Fiordelisi et al., 2014). Fiordelisi et al. (2014) estimate abnormal returns to monetary policy news both for broad equity market indices and for individual stock prices of globally systemically important financial institutions (G-SIFI). The authors consider G-SIFIs in the EA, Japan, Switzerland, the UK, and the US. Fiordelisi et al. (2014) show that these individual stock prices react positively to monetary easing announcements, which also holds for broad equity indices. Interestingly, while the overall stock markets seem to decline around restrictive interventions or inaction, G-SIFIs show positive abnormal returns for some event windows (Fiordelisi et al., 2014).

Ricci (2015) estimates cumulative abnormal returns (CAR) of European bank stocks with a standard market model. The author finds, consistent with Fiordelisi et al. (2014), that bank stocks react more strongly to announcements concerning non-conventional policies than to traditional (interest rate) announcements, and CARs exhibit a high degree of heterogeneity. Moreover, there is evidence that bank characteristics (e.g., risk-exposure, balance-sheet quality) influence the stock price response to monetary policy announcements (Ricci, 2015).

English et al. (2018) study the effects of FOMC announcements on stock prices and accounting measures of profitability using US data from 1997 to 2007. They find that positive level and slope surprises, i.e., higher interest rates and a steeper yield curve, reduce the price of bank stocks. The negative slope effect is less pronounced for banks engaging more in maturity transformation (English et al., 2018). It is questionable whether these results can be applied to the European banking sector, as non-interest income is relatively low compared to their transatlantic peers (Claessens et al., 2018, p. 3).

Two recent studies build on the methodology of Jarociński and Karadi (2020) and focus on ECB announcements. Kerssenfischer (2019) finds information effects to be crucial in understanding financial market responses to ECB communication. In a related study, Jung and Uhlig (2019) show that ECB announcements steepening the yield curve have beneficial effects on bank health indicators. Both studies find a negative impact of the monetary policy on bank stocks, and a positive effect of the central bank information shock, which results - given the positive correlation between bank stocks and the overall market - primarily from the identifying assumption.

Our paper is also closely related to Ampudia and Van den Heuvel (2019) who investigate the influence of ECB monetary policy on the stock valuations of EA banks from 1999 to 2016 using high-frequency data. They proxy monetary surprises by changes in 1 month and 2 year EONIA swap rates. Consistent with the existing literature, they find on average, that a 25 BP cut in the short-term rate increases stock prices by approximately 1%. Noteworthy, this relationship reverses in the low interest rate environment as EA bank stocks suffer from negative surprises in the short-term rate from 2012 on. This effect is more pronounced for banks depending to a greater extent on deposit funding. In contrast, the positive surprises in the long-term rate (tightening) affects stock valuations negatively throughout the entire sample, however, not always significantly (Ampudia and Van den Heuvel, 2019).

2.2.2 Monetary Policy and Bank Profitability

Some recent papers focus on the relationship between monetary policy and bank profitability, especially against the backdrop of the prolonged low interest rate environment.

In a study on large international banks, Borio et al. (2017) detect a positive effect of short-term interest rates as well as the slope of the yield curve on net interest income (NII), while the reverse holds for non-interest income. Moreover, they find evidence for a positive link between provisions and interest rates. Overall banking profitability, measured in return on assets (ROA), is positively affected by higher interest rates as higher NIIs overcompensate the effects in non-interest income and provisioning, and this effect is more pronounced in a low interest rate environment (Borio et al., 2017).

Bikker and Vervliet (2018) study the influence of low interest rates on the profitability of US banks. Higher short-term interest rates increase the net interest margin (NIM), ROA, and return on equity (ROE), while the relationship is negative for overall profits. Bikker and Vervliet (2018) explain this surprising finding by lower provisioning, which may pose an additional threat to financial stability. The adverse effect of low interest rates on the NIM undermines the view that profits from the maturity transformation business, i.e., short-term borrowing and long-term lending, suffer from a prolonged period of low rates.

Consistent with Borio et al. (2017), Altavilla et al. (2018) find monetary easings to have a negative influence on NII and a favorable effect on loan-loss provisioning costs and non-interest income. However, in their study, a cut in short-term rates and a reduction in the slope of the yield curve results only in weaker profitability in terms of ROA if the endogeneity of monetary policy with respect to certain financial and economic conditions is not considered. Altavilla et al. (2018) explain the limited impact of monetary policy on profitability by offsetting effects in the NII and provisions. However, they argue that a very long period of low interest rates can harm bank profitability. Turning to a market-based view, reductions in short-term rates and non-standard monetary easing decision are associated with positive stock price reactions (Altavilla et al., 2018).

English et al. (2018) reveal that the relationship between the level of interest rates and profitability measured as NII and net income is positive in the short run, however, turning to negative after four quarters. Besides these level effects, they find a positive influence of a steeper yield curve on NII and net income. At first glance, this contradicts their results concerning stock prices, according to which a higher slope leads to a decrease in market valuation (see above). However, they explain these inconsistencies by different time horizons and the consideration of discounting effects in stock prices (English et al., 2018).

Claessens et al. (2018) study the influence of interest rates on NIMs and profitability (ROA) using a large sample of banks from 47 countries over the period from 2005 to 2013. In addition, they look closely at how a low-for-long period affects profitability measures. They find that a reduction in interest rates narrows the NIM, and the effect is more pronounced when rates are at a low level. Moreover, overall profitability is also negatively affected by the low interest rate environment (Claessens et al., 2018).

2.3 Data and Identification

2.3.1 Timing and Timeline of ECB Announcements

In the early phase of the Eurosystem, from 1999 until late 2001, the ECB took two monetary policy decisions per month. During this period, there were many decisions not accompanied by a press conference. Thereafter, the Eurosystem moved to a monthly rhythm, usually holding a press conference. Since 2015, the interval between monetary policy decisions has regularly been six weeks.[3]

The ECB's monetary policy announcement is divided into two sections (see figure 2.1). During the considered period, at 13:45 Frankfurt time (CET or CEST), the decision is published as part of a press release on the homepage. At 14:30, the press conference begins and lasts approximately one hour. The press conference consists of the introductory statement, which the ECB president reads out, and a Q&A session.[4]

Choosing the correct window size is not trivial for researchers. As pointed out by Rogers et al. (2014), movements in asset prices also contain news not originating from the central bank if the window is too large. On the contrary, if the windows are too tight, monetary news might not be fully priced in. In this paper, we measure asset price reactions in the "monetary event window" as defined in Altavilla et al. (2019) and shown in figure 2.1, covering the announcement of the policy decision, i.e., the publication of the press release, and the entire press conference.

Table 2.1 shows bivariate correlations of financial surprises during the "monetary event window" on days when the ECB governing council took a decision. Data is presented for the entire period under consideration (January 1999 - March 2021), the pre-crisis sample (January 1999 - August 2008), and the post-crisis sample (September 2008 - March 2021). We choose September 2008 as the cutoff due to the

[3]The exact dates and intervals between the decisions can be found on the ECB's website and in the EA-MPD dataset compiled by Altavilla et al. (2019).

[4]The times of the publication process have been changed in 2022. Beginning with the governing council meeting on July 21, 2022, the ECB publishes its monetary policy decision at 14:15 and starts the press conference at 14:45 (European Central Bank (ECB), 2022a).

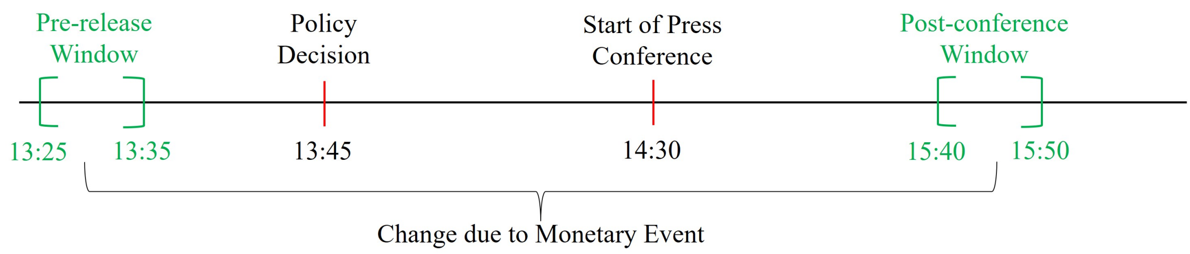


Figure 2.1: ECB communication timeline

Notes: Window definition based on Altavilla et al. (2019).

bankruptcy of Lehman Brothers. Overall, the short-term interest rates (OIS_1M) are moderately negatively correlated with stock prices. After the financial crisis, the relationship was weaker for banking stocks (SX7E) than the overall stock market (STOXX50). Considering long-term interest rates (DE10Y) in the post-crisis era, we see a (weak) positive correlation for banking stocks (SX7E), and a negative correlation for the stock market (STOXX50). As shown in table 2.8 (appendix), coefficients of correlation are sensitive to outliers. If we drop values below the 1% and above the 99% percentile, coefficients of correlation change. However, important ordinal connections remain valid: First, we see less negative co-movement between the short-term interest rate (OIS_1M) and the bank stock index (SX7E) after the financial crisis (compared to STOXX50). Second, after the financial crisis, the correlation between long-term rates and bank stocks is higher compared to the overall market.

2.3.2 Identification of Shocks

For the identification, we build on the considerations of Jarociński and Karadi (2020), and for the implementation, in particular, on Jarociński (2020) in constructing structural shocks transmitted to financial markets during ECB monetary policy announcements. Interest rate surprises during announcements are disintegrated into two orthogonal shocks. While the monetary policy shock is associated with a negative

Table 2.1: Correlations of financial variables during monetary events

Pre financial crisis: January 1999 - August 2008 (151 observations)					
	OIS_1M	OIS_1Y	DE10Y	STOXX50	SX7E
OIS_1M	1.0000				
OIS_1Y	0.5374	1.0000			
DE10Y	0.0519	0.5941	1.0000		
STOXX50	-0.1390	-0.0555	0.0858	1.0000	
SX7E	-0.1606	-0.1153	0.0542	0.8923	1.0000
Post financial crisis: September 2008 - March 2021 (127 observations)					
	OIS_1M	OIS_1Y	DE10Y	STOXX50	SX7E
OIS_1M	1.0000				
OIS_1Y	0.5997	1.0000			
DE10Y	0.1261	0.5261	1.0000		
STOXX50	-0.3318	-0.1848	-0.1381	1.0000	
SX7E	-0.2394	-0.1259	0.0801	0.8626	1.0000
Full sample: January 1999 - March 2021 (278 observations)					
	OIS_1M	OIS_1Y	DE10Y	STOXX50	SX7E
OIS_1M	1.0000				
OIS_1Y	0.5585	1.0000			
DE10Y	0.0849	0.5395	1.0000		
STOXX50	-0.2240	-0.1212	-0.0675	1.0000	
SX7E	-0.1754	-0.1027	0.0671	0.8395	1.0000

Notes: The table shows the correlation of changes in the 1 month OIS rate (OIS_1M), 1 year OIS rate (OIS_1Y), 10 years German government bond rate (DE10Y), EURO STOXX 50 Index (STOXX50), and EURO STOXX Banks Index (SX7E) during windows around monetary policy events. The underlying data was taken from the Euro Area Monetary Policy event study Database (EA-MPD) which was constructed by Altavilla et al. (2019). Correlations are based on the "monetary event window", in which changes are calculated from median quotes in 13:25-13:35 CET and 15:40-15:50 CET. The sample is divided into a pre financial crisis and post financial crisis subsample in September 2008 (bankruptcy of Lehman Brothers).

co-movement of interest rates and the stock market, the central bank information shock loads positively on the stock market, i.e., interest rates and the stock market react in the same direction (Jarociński and Karadi, 2020).

Table 2.2: Sign restrictions

Variable	Monetary policy	Central bank information	Slope
Interest rates	+	+	*
Stock market	-	+	*

Source: Jarociński and Karadi (2020) and own extensions.

We extend the methodology of Jarociński (2020) by considering an additional third factor to investigate the relationship between surprises in the slope of the yield curve and bank stock prices. As shown in table 2.2, we do not imply ex-ante sign restrictions for the slope factor in order to investigate the sign of the effect empirically.

Following Jarociński (2020), we first construct a $T \times 2$ matrix M which contains the interest rate and stock market surprise in a narrow window around the monetary announcements,

$$M = (i^{Total}, s)$$

where i^{Total} is a $T \times 1$ vector of the first principal component of the change in market interest rates of different maturities and s is a $T \times 1$ vector of stock market surprises during the event window. Generalizing Jarociński (2020), who considers the one month, three month, six month, and one year OIS rate, we also include the 10 year German government bond rate as we are interested in reactions to changes in the slope of the yield curve.[5] We keep the second principal component because it has the following valuable properties. As shown in table 2.3, factor loadings are negative for short-term interest rates and positive for the long-term rate. The loadings increase with maturity. This allows us to interpret the second unrotated principal component as a slope factor, i^{Slope}.[6]

The matrix of surprises M is now decomposed into a $T \times 2$ matrix U of orthogonal shocks and a 2×2 matrix C satisfying the sign restrictions

[5] We follow Jarociński (2020) and rescale the standard deviation of the first principal component with respect to the 1 year OIS rate.

[6] We adapt the original code for the calculation of shocks, which was available on Marek Jarociński's website. We also drop the (internationally) coordinated announcements on 09/13/2001, 09/17/2001 (both after the terrorist attacks on the US), and 10/08/2008 (financial crisis). The underlying data on interest rates and the stock price index are taken from the EA-MPD dataset of Altavilla et al. (2019) ("monetary event window"), available at `https://www.ecb.europa.eu/pub/pdf/annex/Dataset_EA-MPD.xlsx`, data until March 2021.

$$M = UC, \text{ where } U = (i^{MP}, i^{CBI}), \; (i^{MP})' i^{CBI} = 0 \text{ and } C = \begin{pmatrix} 1 & c_{MP} < 0 \\ 1 & c_{CBI} > 0 \end{pmatrix}.$$

i^{MP} and i^{CBI} denote the two orthogonal monetary policy and central bank information shock, respectively.

We follow again Jarociński (2020) for the decomposition into orthogonal components and their subsequent rotation. Using the QR decomposition, the matrix of surprises is decomposed into the $T \times 2$ orthogonal matrix Q and the 2×2 upper triangular matrix R,

$$M = QR, \text{ where } Q'Q = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \text{ and } R = \begin{pmatrix} r_{11} > 0 & r_{12} < 0 \\ 0 & r_{22} > 0 \end{pmatrix}.$$

As in Jarociński (2020), we impose positive diagonal elements of R by (pre)multiplying Q and R by the 2×2 matrix $S = diag(sgn(diag(R)))$ and the rotation matrix P is given by

$$P = \begin{pmatrix} \cos(\alpha) & \sin(\alpha) \\ -\sin(\alpha) & \cos(\alpha) \end{pmatrix}$$

where α is the median rotation angle,[7]

$$\alpha = 0.5 * \arctan(\frac{-r_{22}}{r_{12}}) \text{ if } r_{12} \leq 0,$$
$$\alpha = 0.5 * \arctan(\frac{r_{12}}{r_{22}}) + 0.5 * \frac{\pi}{2} \text{ if } r_{12} > 0.$$

Still following Jarociński (2020), we rescale the orthogonal components with the 2×2 matrix D

[7] In the baseline, Jarociński (2020) derives the rotation angle from the desired variance share, $var(i^{MP})/var(i^{Total})$, i.e., the variance of the monetary policy shocks relative to the variance of the first principal component of interest rate surprises.

$$D = \begin{pmatrix} r_{11}\cos(\alpha) & 0 \\ 0 & r_{11}\sin(\alpha) \end{pmatrix}$$

to ensure that the sum of both structural components equals the total interest surprise during the "monetary event window", i.e.,

$$i^{Total} = i^{MP} + i^{CBI}.$$

Therefore, Jarociński (2020) computes U and C as

$$U = QPD \text{ and } C = D^{-1}P'R.$$

Table 2.3: Factor loadings

Instrument	PC1	PC2
OIS_1M	0.41	-0.48
OIS_3M	0.50	-0.21
OIS_6M	0.51	-0.02
OIS_1Y	0.49	0.17
DE10Y	0.28	0.83

Source: Factor loadings were calculated using the "monetary event window" in the EA-MPD dataset of Altavilla et al. (2019).

Figure 2.2 depicts the monetary policy (MP), the central bank information (CBI) shock, and the slope surprise for the days when the governing council took a monetary policy decision.

In the following, we will briefly discuss three announcements that have produced strong effects. We see a strong negative value for the central bank information shock during the European SDC on August 4, 2011. In the introductory statement, the then ECB president Jean-Claude Trichet emphasized the high uncertainty with respect to the economic outlook (European Central Bank (ECB), 2011). Although

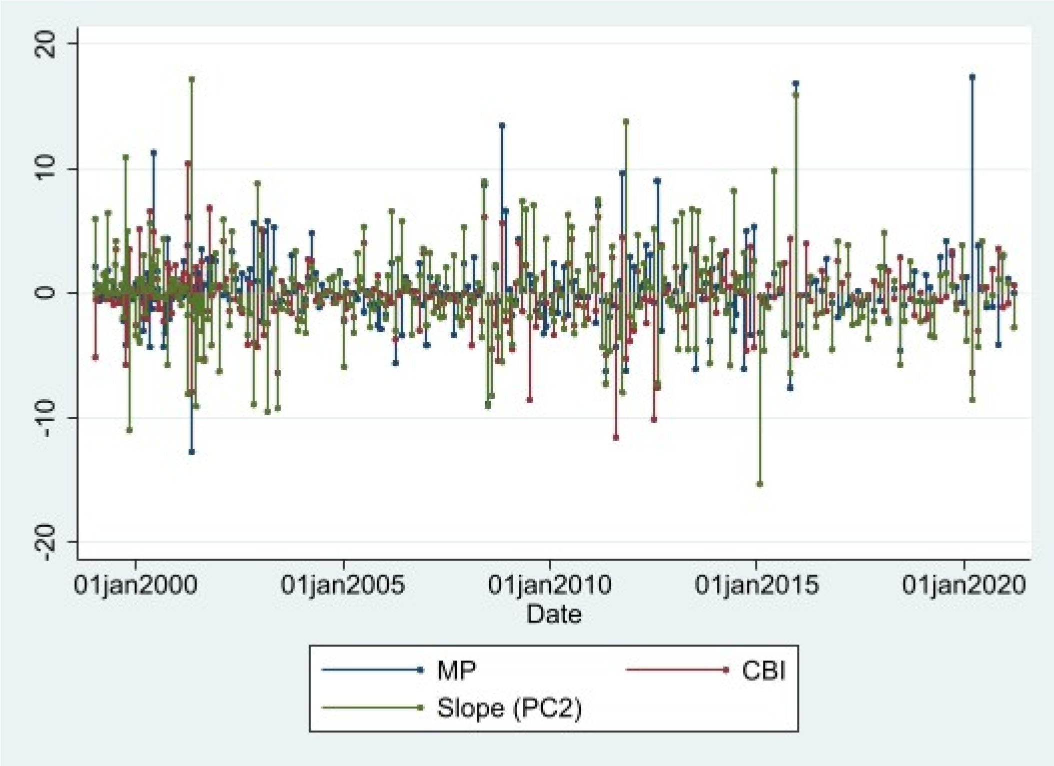


Figure 2.2: Monetary policy, central bank information shock and slope factor

the key interest rates have been kept unchanged, the announcement resulted in a negative interest rate surprise. As discussed in Jarociński and Karadi (2018), the announcement contained negative (economic) news, leading to same-sign reactions in market interest rates and stock markets.

On January 22, 2015, a pronounced (negative) slope surprise occurred due to the announcement of the ECB's expanded asset purchase programme (European Central Bank (ECB), 2015). While short-term rates did not show substantial movements, long-term interest rates declined significantly. This can be explained by the fact that the announced purchase of government bonds led to a corresponding increase in the demand for these securities and an associated decline in long-term yields. As a result, the slope of the yield curve reduced considerably.

On March 12, 2020, when the stock market had already plummeted due to the COVID-19 pandemic, the ECB announced a package of measures to stabilize the economy. However, the monetary stimulus probably fell short of market expectations

(Bernoth et al., 2020), leading to a rise in market interest rates and a further slump in the equity markets. These reactions are reflected in a high value for the monetary policy shock.

2.3.3 Bank-level Stock Data

Our sample consists of large, listed banks in the European Union. The banks were selected according to their market capitalization. To avoid double counting the same bank by considering different entities of one banking group, we excluded local subsidiary banks that are majority controlled by the parent.[8] In principle, we consider the period from 2000 to 2021. However, we do not have the complete time series for all banks, e.g., some banks have only been listed later.

To rule out endogeneity and omitted variable problems as much as possible, we consider reactions of bank stocks in a narrow window around the monetary policy announcement as described above. To do so, we took high frequency (by minute) data on bank stocks from the Refinitiv Tick History database and calculated the stock price reaction r_t, in line with Altavilla et al. (2019), as the difference between the median stock price[9] $\tilde{S}_t$ in the "pre-release window", 13:25-13:35 CET/CEST, and the median price in the "post-conference window", 15:40-15:50 CET/CEST,

$$r_t = [ln(\tilde{S}_t^{\text{Post-conference}}) - ln(\tilde{S}_t^{\text{Pre-release}})] * 100, \tag{2.1}$$

where index t runs over monetary events.[10] In more than 10% of cases, the return

[8] In more detail, we used the advanced search of Refinitiv Eikon equity universe and applied the following filters: (i) we restricted equity instruments to primary issues, (ii) we included ordinary shares only, (iii) we included only shares issued in the European Union, (iv) we restricted the sample to bank stocks, (v) we dropped banks with very low trading volumes, i.e., stocks with average daily volumes (30 days) below 10,000 as per August 2021. We finally restricted the sample to stocks with at least USD 1 bn in market capitalization and dropped banks that started trading later than 2017.

[9] The underlying pricing data is unadjusted which means that stock splits and rights issues lead to relevant changes in market prices that do not reflect fundamental market behavior. This could strongly influence daily returns calculated on the basis of daily closing prices. However, this is not a problem for our identification as we use intraday returns. Also, the currency for price quotes changed in some instances, e.g., from the previous local currency to Euro.

[10] To reduce the number of calculation steps for the data on single securities, the windows are

observation is missing as a result of an insufficient frequency in some price series, i.e., when there was no trade price available in the "pre-release window" or the "post-conference window".

To explore if bank stocks react systematically differently to ECB monetary policy announcements than the general stock market, we select a control sample. All companies from the STOXX Europe 50 Index that are not in the bank sample and headquartered in the EU are selected for this purpose.[11]

2.4 Estimation

2.4.1 Individual Bank Stock Returns

In this section, we investigate the effects of ECB announcements on the stock returns of individual banks. In more detail, we are studying the influence of the monetary policy and central bank information shocks and the slope factor on price movements of European bank stocks. The following regression equation is estimated by OLS:

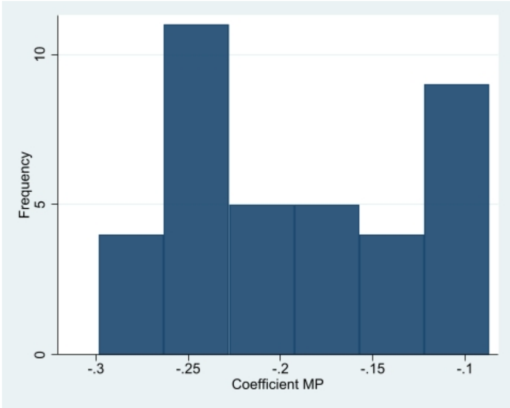
$$r_t = \alpha + \beta_1 i_t^{MP} + \beta_2 i_t^{CBI} + \beta_3 i_t^{Slope} + \epsilon_t, \tag{2.2}$$

where r_t is the respective logarithmic return during the "monetary event window", α the constant, i_t^{MP} the monetary policy shock, i_t^{CBI} the central bank information shock, i_t^{Slope} the slope factor, and ϵ_t the error term. Please note that observations are disjoint and irregularly spaced across time, which makes serial correlation in the error highly unlikely (English et al., 2018, p. 84).

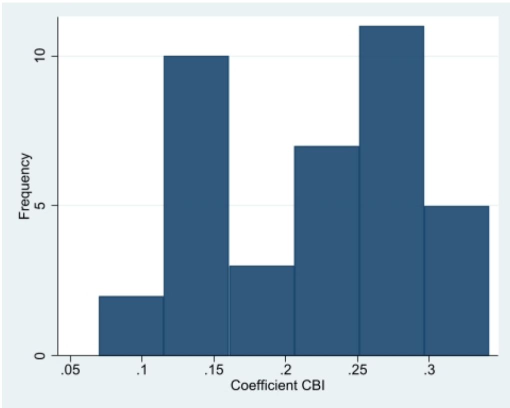
Estimating the relationship for each bank separately allows us to reveal potential heterogeneity in the betas of shocks transmitted via ECB communication. Due to

always calculated with the times described above, even if no press conference has taken place.

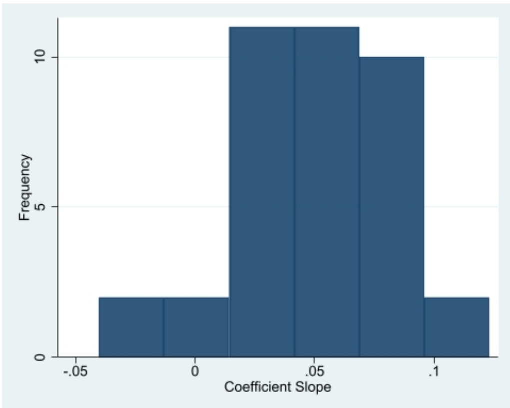
[11] Foos et al. (2022) chose a similar approach in order to determine if observed effects are bank-specific. In addition to the companies selected according to the selection criteria described above, we included the share of Linde plc in our sample as it was also listed in the leading German stock market index.



(a) Monetary Policy (MP)

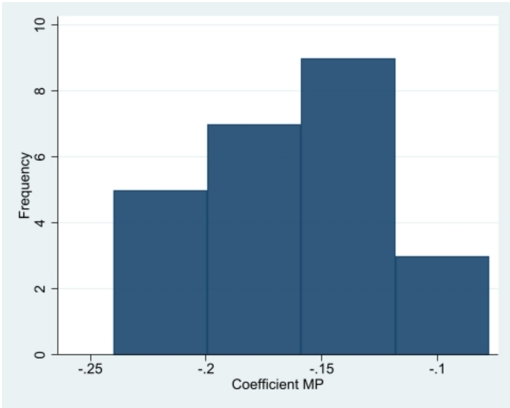


(b) Central Bank Information (CBI)

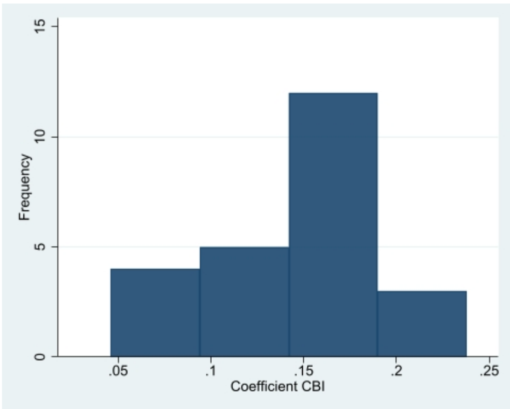


(c) Slope

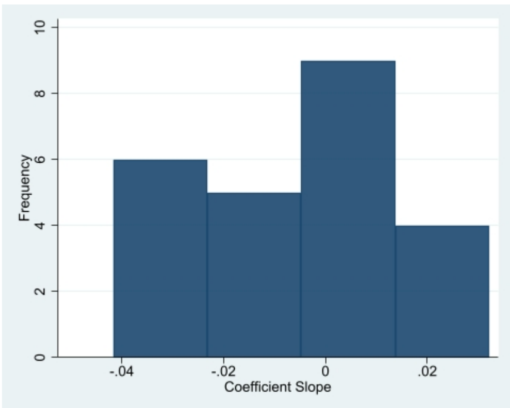
Figure 2.3: Histogram of point estimates, banks



(a) Monetary Policy (MP)



(b) Central Bank Information (CBI)



(c) Slope

Figure 2.4: Histogram of point estimates, control group

the sign restrictions between the interest rate surprises and the reaction of the overall stock market, as explained in section 2.3.2, and given the typically high correlation between stock markets and banking stocks, we expect in general a negative coefficient for the monetary policy shock. Accordingly, the coefficient of the central bank information shock is expected to be positive. Good news about the economic outlook transmitted via ECB communication, which leads to higher stock market valuations, should also drive bank stock prices up. Given the mixed findings for the role of the yield curve slope in previous literature, we have no a priori expectation for the coefficient of the slope factor.

As a complication, the time series are not always of equal length. For example, some bank shares were not traded until well after 2000 or we do not have the entire price history. If the effects change over time, this can thus complicate the comparability of individual estimates. We restrict the sample as follows to ensure that the coefficients are comparable: First, for individual effects, we only consider observations from the financial crisis (September 2008) to the end of the observation period. Second, we drop results for banks with less than 100 observations to reduce bias from a small sample and a concentration at the end of the observation period. Figure 2.3 depicts the frequency histograms of point estimates of the monetary policy shock, the central bank information shock, and the slope factor, from the individual regressions. The regressions were estimated by including a constant, which is not reported in the output. The constant was statistically insignificant in the vast majority of cases. In line with our expectation, the coefficient of the monetary policy shock is significantly negative for all banks in the sample. This finding is consistent with a tighter monetary policy having an adverse effect on the valuation of European banks. While the sign and the significance are compatible across banks, the size of the coefficients shows substantial heterogeneity. As shown in table 2.4, coefficients of banks not located in the EA have an in absolute terms lower coefficient, i.e., their stocks seem to suffer (benefit) less from a monetary tightening (easing) shock.[12] This finding is in line with the intuition that EA banks are more exposed to ECB decisions. For all banks, the coefficient of the central bank information shock is positive and significant. As the central bank information shock is consistent with a better economic outlook (Jarociński and Karadi, 2020), it increases future expected dividends of banks and increases stock prices. Again, the coefficients' sizes differ substantially, and EA banks seem to react more strongly. The slope coefficients of bank stocks are positive and statistically significant at the 5% level in 23 cases (based on robust standard errors). In contrast, none of the negative coefficients of the slope surprise is statistically significant. These results imply that market surprises that increase the yield curve slope raise European banks' market valuations when controlling for contemporaneous monetary policy and information shocks. Overall, the explanatory power for the stock returns of the different banks varies materially, with R^2s ranging from approximately 0.13 to 0.75. To investigate if bank stocks react systematically differently to ECB announcements than the overall stock market, we compare the results with estimates from companies that are not classified as banks. As shown in figure 2.4 and table 2.4 ("control group"), the stock returns in the control group have a negative coefficient for the monetary policy and a positive coefficient for the central bank information shock. Note that this is partly by construction, as the sign restrictions were imposed with respect to the co-movements of the overall stock market and interest rates. However, the absolute magnitude of coefficients is on average smaller compared to their banking counterparts. In particular, the coefficient of the central bank information shock is considerably higher for EA banks compared to stocks in the control group. This result is consistent with the consideration of Jarociński and Karadi (2020), who find that the central bank information shock might also signal news about the financial sector. Interestingly, very few slope coefficients in the control sample are statistically significant at the 5%

[12] Data on EA membership was verified on the ECB's website (European Central Bank (ECB), 2022b).

level, and they are on average negative.

2.4.2 Pooled Analysis of Bank Stock Returns

To further investigate the fundamental differences in stock price reactions of banks and general stocks, and in particular, to study potential changes over time, we estimate the relationship within a pooled OLS setup. Therefore we separate the sample into three subsamples, namely, the *pre-crisis* period (observations until August 2008), the *post-crisis* period (September 2008-2021), and the *low rates* period (2012-2021).[13] Hence, the low rates period is a subsample of the post-crisis period.

We estimate the model

$$r_{it} = \alpha + \beta_1 i_t^{MP} + \beta_2 i_t^{MP} D_i^{Bank} + \beta_3 i_t^{CBI} + \beta_4 i_t^{CBI} D_i^{Bank} + \beta_5 i_t^{Slope} + \beta_6 i_t^{Slope} D_i^{Bank} + \epsilon_{it}, \tag{2.3}$$

by OLS, where D_i^{Bank} equals one for bank stocks and zero otherwise. Following English et al. (2018, p. 84), we cluster standard errors across the time variable to address potential cross-sectional correlation.

The results for the full sample (specification I and II of table 2.5) confirm the findings from individual bank stock regressions. A positive monetary policy shock decreases stock prices, and a positive central bank information shock increases returns. Consistent with our previous findings, the central bank information effect seems to be significantly more pronounced for banking stocks. The slope coefficient is significant and positive for banks while insignificant and negative for the control group. Please note that in all regressions with interaction terms, the coefficients of MP, CBI, and Slope (PC2) denote the effect for companies in the control group.

[13] September 2008 was chosen as a cutoff for the financial crises as Lehman Brothers filed for bankruptcy this month. In 2012, the governing council set the deposit facility at a non-positive rate for the first time. The time points chosen are similar to those of Ampudia and Van den Heuvel (2019). However, our "post-crisis" sample contains the entire period from September 2008 until March 2021.

The interaction terms give the respective difference of bank stocks. Comparing the different periods, the impact of monetary policy shocks remains relatively stable over time and does not differ significantly between banks and firms not classified as banks. Before September 2008, the price reaction of bank stocks to the CBI shock was slightly weaker compared to other companies. In contrast, banks are more sensitive to the central bank information shock after the financial crisis (specification VI of table 2.5) and even more dependent since 2012 (specification VIII of table 2.5). Concerning the role of the yield curve slope, the results of the pooled OLS regression corroborate the findings from individual regressions: Relative to other stocks, bank stocks seem to profit from a steeper yield curve. Again, the time period under consideration is crucial as we do not see a significant difference in the pre-crisis sample.

Overall, the absolute values of coefficients increase from the pre-crisis period to the post-crisis period (specification III and V of table 2.5). In addition, the explanatory power is considerably higher in the post-crisis sample. Hence, stock investors seem to be more sensitive to ECB communication after the financial crisis compared to pre-crisis times. This indicates a change in the transmission of monetary policy impulses and may thus be relevant for the effectiveness of central bank policy.

Table 2.4: OLS regression summary - individual stocks

	Mean	Min	Max	N	+ Sig. 5%	- Sig. 5%
Monetary Policy (MP)						
Banks	-0.192	-0.298	-0.087	38	0	38
Banks EA	-0.217	-0.298	-0.110	29	0	29
Banks non-EA	-0.111	-0.137	-0.087	9	0	9
Control group	-0.162	-0.240	-0.078	24	0	23
Central Bank Information (CBI)						
Banks	0.221	0.070	0.342	38	38	0
Banks EA	0.250	0.138	0.342	29	29	0
Banks non-EA	0.128	0.070	0.159	9	9	0
Control group	0.144	0.046	0.238	24	22	0
Slope						
Banks	0.049	-0.040	0.123	38	23	0
Banks EA	0.056	-0.040	0.123	29	21	0
Banks non-EA	0.030	0.017	0.046	9	2	0
Control group	-0.005	-0.042	0.032	24	1	2
Explanatory Power R^2						
Banks	0.506	0.131	0.751	38		
Banks EA	0.528	0.131	0.751	29		
Banks non-EA	0.434	0.270	0.592	9		
Control group	0.661	0.229	0.838	24		

Notes: The table shows summary statistics of OLS coefficients of individual bank stocks. + Sig. 5% (- Sig. 5%) report the number of coefficients which are positive (negative) and significant at the 5% level. P-values are based on robust standard errors. The results are based on the "monetary event window", in which changes are calculated from median prices/quotes in 13:25-13:35 CET/CEST and 15:40-15:50 CET/CEST. The samples contain observations from September 2008 until March 2021.

Table 2.5: Pooled OLS regression

	I	II	III	IV	V	VI	VII	VIII
Sample	Full	Full	Pre-crisis	Pre-crisis	Post-crisis	Post-crisis	Low rates	Low rates
MP	-0.169***	-0.154***	-0.138***	-0.146***	-0.175***	-0.157***	-0.159***	-0.164***
	(0.0134)	(0.00490)	(0.0120)	(0.00960)	(0.0159)	(0.00514)	(0.0241)	(0.00706)
CBI	0.171***	0.143***	0.127***	0.142***	0.188***	0.140***	0.227***	0.124***
	(0.0114)	(0.00545)	(0.0108)	(0.0102)	(0.0154)	(0.00677)	(0.0233)	(0.0102)
Slope (PC2)	0.0197**	-0.00254	0.00526	0.00475	0.0315***	-0.00627*	0.0402***	-0.00795**
	(0.00803)	(0.00357)	(0.00682)	(0.00694)	(0.0114)	(0.00352)	(0.0133)	(0.00374)
Bank#MP		-0.0234		0.0147		-0.0276		0.00997
		(0.0237)		(0.0160)		(0.0286)		(0.0409)
Bank#CBI		0.0464**		-0.0291*		0.0775**		0.164***
		(0.0227)		(0.0165)		(0.0322)		(0.0499)
Bank#Slope		0.0373**		0.00111		0.0596***		0.0748***
		(0.0157)		(0.0124)		(0.0213)		(0.0231)
Constant	-0.0248	-0.0255	-0.000992	-0.00113	-0.0467*	-0.0471*	-0.0433	-0.0437
	(0.0188)	(0.0187)	(0.0227)	(0.0228)	(0.0268)	(0.0267)	(0.0324)	(0.0322)
Observations	14,812	14,812	6,328	6,328	8,484	8,484	5,987	5,987
R-squared	0.382	0.390	0.227	0.228	0.439	0.455	0.483	0.509

Notes: The table shows OLS coefficients and their respective standard errors (clustered by time). Significance levels: *** 1%, ** 5%, * 10%. The results are based on the "monetary event window", in which changes are calculated from median prices/quotes in 13:25-13:35 CET/CEST and 15:40-15:50 CET/CEST.

2.4.3 Discussion

We address (i) if bank stocks react systematically differently to shocks transmitted by monetary policy announcements than the overall stock market and (ii) if bank stocks react immediately to surprises in the slope of the yield curve. Against the background of the findings in this section, the answers to both questions depend largely on the period under consideration.

Consistent with the recent literature on high-frequency identification of monetary shocks (Andrade and Ferroni, 2021; Miranda-Agrippino and Ricco, 2021; Jarociński and Karadi, 2020; Cieslak and Schrimpf, 2019), we find that disentangling pure monetary from information shocks in market interest rate surprises during central bank announcements is crucial for investigating asset price responses. Qualitatively, i.e., in terms of sign and significance, these effects are the same for all companies. However, there is evidence that information shocks are more relevant for bank stocks, especially after the financial crisis. In the remainder of this section, we will discuss potential drivers of the results in section 2.4.1 and section 2.4.2.

Monetary Policy and Central Bank Information Shocks

When controlling for contemporaneous central bank information effects by following the identifying assumptions of Jarociński and Karadi (2020), a monetary policy tightening is clearly and unambiguously associated with a decline in stock prices. This finding is consistent with the recent literature, see e.g., Jarociński and Karadi (2020), Altavilla et al. (2019), Cieslak and Schrimpf (2019), Andrade and Ferroni (2021), and, Miranda-Agrippino and Ricco (2021). While the general relationship between (pure) monetary policy shocks and the stock market is - given the sign restrictions in the identification - not surprising, it is noteworthy that a positive monetary policy shock leads to a decline for all individual bank stock prices when considering data since the financial crisis (subsection 2.4.1). The pooled analysis (subsection

2.4.2) reveals a relatively stable effect over time, changing only moderately from the pre-crisis period to the post-crisis period. Moreover, bank stocks do not seem to react differently to pure monetary policy shocks than firms in the control group. Concerning a monetary policy tightening, we cannot identify a bank-specific effect on stock prices. First, this seems surprising given reported relationships between interest rates on the one hand and NII and NIM on the other hand as there could be a positive relationship between these earnings measures and interest rates, at least in the low interest rate environment (Borio et al., 2017; Altavilla et al., 2018; Bikker and Vervliet, 2018; English et al., 2018; Claessens et al., 2018). However, the reason might be discounting effects or changing expectations about profits in the more distant future (e.g., English et al., 2018, p. 95). A positive central bank information shock is associated with higher stock prices, for banks as well as for stocks in the control group. The positive stock market reaction is in line with intuition, as the central bank information shock has similar properties to positive news about the economy (Jarociński, 2020). Unlike the monetary policy shock, the sensitivity of bank stocks to the information shock changes substantially over time while the effect for firms in the control group remains relatively stable. In more detail, bank stocks react more strongly (positively) to the information shock after the financial crisis and even more pronounced during the low interest rate environment. This finding is in line with Kerssenfischer (2019, p. 8) as his information shock coefficient was higher for banks than for the general stock market. According to Jarociński and Karadi (2020, p. 30), "... the central bank information shock is consistent with news about the state of the financial intermediary sector or, more broadly, the financial market conditions". After the turmoil of the financial crisis and the ongoing debate on weak profitability in the financial sector, bank stock investors may listen more closely to information and signals issued during ECB monetary policy announcements.

Surprises in the slope of the yield curve

When controlling for monetary policy and central bank information shocks, individual bank stocks benefit from slope surprises, as shown in section 2.4.1. In the control sample, the direction of the effect is vague and generally insignificant. As the results in section 2.4.2 imply, the slope is relevant for bank stocks after the financial crisis and, again, even more important in the low interest rate environment. At first glance, the results seem to contradict English et al. (2018) identifying a negative impact of level surprises and slope surprises on bank stocks. However, their study refers to US data up to 2007, and our results indicate that slope effects do not seem to matter before the financial crisis. Moreover, European banks generate a relatively small portion of their revenues from non-interest income (Claessens et al., 2018, p. 3), which makes the traditional maturity transformation business more critical. Furthermore, our results seem to contradict those of Ampudia and Van den Heuvel (2019, p. 14), who find a positive effect of the short-term interest rate and a negative one of the long-term interest rate after the financial crisis. However, our approach differs in two important respects: First, we relate the results to the entire monetary policy event (press release and press conference), while Ampudia and Van den Heuvel (2019) focus on the time window around the press release. Second, following Jarociński and Karadi (2020), we control for the role of (pure) monetary and information effects. In contrast, our findings are in line with Jung and Uhlig (2019), who find a positive effect of the slope on the soundness of EA banks, however, using a different identification. Our results are also consistent with recent findings concerning the role of a prolonged low interest rate environment for bank (accounting) profitability. Altavilla et al. (2018) state that an extended period of low interest rates is adverse for bank profits if the economy is already in a low interest rate environment for a long time. Similarly, Claessens et al. (2018) show evidence of a negative effect of a prolonged period of low interest rates on bank profitability.

2.5 Heterogeneity

The results in section 2.4 show that bank stocks react heterogeneous to monetary announcements. In this section, we explore potential reasons for the heterogeneity. Due to the small sample size, we are focusing on comparing mean coefficients by bank characteristics. We perform statistical tests to evaluate if the mean coefficients grouped by different bank characteristics differ significantly. As in the analysis of section 2.4.1 we concentrate on the period after the financial crises.[14] Based on theoretical considerations and the empirical literature, we formulate hypotheses on the role of bank size, the importance of deposits as a source of funding, and interest rate adjustment practices in different countries. As the reactions of EA and non-EA banks are very different, we focus on bank stocks in the EA.

Bank size (Total Asset)[15]

A natural candidate for a relevant variable driving heterogeneous responses is size, measured in market value or total (balance sheet) assets. Thorbecke (1997, p. 644) states that stocks of small firms are generally more exposed to monetary policy shocks. Large firms are typically better collateralized and, therefore, less constrained by credit conditions (Thorbecke, 1997, p. 644). It is highly questionable if this consideration also applies to banks, especially in the low interest rate environment. Banks can refinance directly with the central bank. Moreover, the allocation of base money has become more expansionary ("full allotment policy"). It is therefore unlikely that credit constraints play a more substantial role for smaller listed banks compared to larger banks. Madura and Schnusenberg (2000, p. 439) and English et al. (2018, p. 89) find that large bank are more exposed to surprises in the level of

[14]Analogous to the previous definition, we consider observations from September 2008 for the calculation of the mean coefficients.

[15]Bank size is measured by the natural logarithm of mean total assets, standardized in Euro. The mean of total assets was calculated as the average of available data from 2008 to 2020. Data was retrieved from Refinitiv Eikon.

interest rates. A possible explanation is that financial markets are taking a closer look at big banks. They are scrutinized by more investors and analysts than small banks. Trading takes place more quickly, and adjustments can be stronger and faster than for shares of small banks.

H1: Stocks of large banks react quantitatively similarly to monetary announcements as stocks of small banks.

Deposit ratio[16]

The link between deposits and the effect of monetary policy shocks on stock prices is not uncontroversial in the literature. For example, Ricci (2015, p. 250) regards the share of deposits (customer deposits/total short-term funding) as a liquidity measure and argues that more liquid banks should be less affected by monetary policy surprises. In fact, she finds a negative relationship between abnormal returns and the deposit share in expansionary announcements (Ricci, 2015, p. 251). In contrast, English et al. (2018) show that stocks of deposit-intensive banks react significantly stronger to interest rate surprises from monetary policy interventions. They argue for a quantity-driven effect, i.e., the ratio of core deposits shrinks, and non-core liabilities increase following a monetary tightening. This could lead to a situation where banks with a high deposit share are more adversely affected by higher interest rates even though deposit rates are typically low compared to other funding sources (English et al., 2018, p. 95). Ampudia and Van den Heuvel (2019) find that banks with high deposit ratios (relative to total assets) are significantly more exposed to short-term interest rate surprises in the low rate environment. Noteworthy, the relationship is positive, e.g., higher short-term rates are associated with higher stock prices when the general level of interest rates is low. They explain this pattern by the existence

[16]The deposit ratio is constructed as the share of total deposits relative to total liabilities. The mean value is calculated as the average of available data from 2008 to 2020. Data was retrieved from Refinitiv Eikon.

of a "reversal rate" (Brunnermeier and Koby, 2018) effect in which an interest rate cut becomes restrictive, i.e., when beneficial valuation effects are overcompensated by an adverse impact on the NII.

H2: Stocks of highly deposit-intensive banks react quantitatively similar to monetary announcements as less deposit-intensive banks.

Fixed vs. variable-rate practices[17]

Within the EA, practices of fixing rates for a loan contract differ substantially. These business practices, i.e., fixed- vs. variable-rate contracts, are a crucial driver for the interest rate risk carried by banks (Hofmann et al., 2018, p. 181). Countries in which fixed-rate contracts dominate are Belgium, France, and Germany. Countries in which loan contracts carry predominately variable rates are Austria, Finland, Greece, Ireland, Italy, Portugal, and Spain. Compared to banks in variable-rate countries, institutions operating in fixed-rate countries are more likely to hold long-term fixed-rate assets such as fixed-rate mortgages. Thus, maturity mismatch is generally higher and these banks are more subject to interest rate risk (Hofmann et al., 2018, p. 181). Ampudia and Van den Heuvel (2019, pp. 22-23) find evidence that this relationship is also visible in bank stock reactions to interest rate surprises: Stocks of banks operating in countries where fixed-rate loans are more prevalent are more sensitive to restrictive monetary policy.

H3: Stock of banks in fixed-rate countries react quantitatively similar to stocks of banks in variable-rate countries.

Table 2.6 reports the results of two-sample t-tests comparing mean coefficients of the monetary policy shock, the central bank information shock, and the slope surprise.

[17] We classified the rate fixation practices in EA countries according to Hofmann et al. (2018).

Table 2.6: Two-sample t-tests on average coefficients

Variable		MP	CBI	Slope (PC2)
Total asset (log)	≤ Median	-0.197	0.228	0.044
	>Median	-0.238	0.273	0.068
	t	2.483	-2.427	-1.796
	p	0.020	0.022	0.084
	DF	27	27	27
Deposit ratio	≤ Median	-0.242	0.276	0.068
	>Median	-0.197	0.232	0.045
	t	-2.752	2.536	1.610
	p	0.011	0.018	0.119
	DF	26	26	26
Rate fixing	variable	-0.208	0.243	0.052
	fixed	-0.245	0.270	0.067
	t	1.850	-1.119	-0.939
	p	0.075	0.273	0.356
	DF	27	27	27

Notes: The t-test tests the null hypothesis that mean coefficients in the groups are equal. Mean coefficients for the different groups are reported. t denotes the test statistic, p the two-sided p-value, and DF the degrees of freedom.

The subsamples are based on the bank characteristics as described above. For size (log of total assets) and the deposit ratio (total deposit relative to total liabilities), we formed two groups: The first group consists of banks with the respective values smaller or equal to the median. The second group contains institutions with values above the median. As a consequence, the two groups based on total assets and deposit ratio are (almost) equally sized, while more banks are located in countries where variable-rate contracts dominate.

Consistent with the findings of English et al. (2018) and Madura and Schnusenberg (2000), large banks are more exposed to monetary policy announcements as mean coefficients of the (pure) monetary policy shock, the central bank information shock, and the slope surprise are in absolute terms significantly higher for larger banks.

Table 2.7: Cross-country heterogeneity

Country	MP	CBI	Slope (PC2)	Banks	R^2
AT	-0.173	0.214	0.068	2	0.57
BE	-0.248	0.230	0.077	1	0.61
DE	-0.245	0.247	0.075	3	0.55
ES	-0.230	0.273	0.074	5	0.61
FI	-0.110	0.159	0.027	1	0.52
FR	-0.245	0.306	0.057	3	0.71
GR	-0.187	0.246	-0.022	4	0.20
IE	-0.244	0.205	0.102	1	0.37
IT	-0.230	0.258	0.064	8	0.58
PT	-0.134	0.151	0.081	1	0.39

Notes: The table reports average coefficients by country, the number of considered banks in the respective country and the average coefficient of determination.

Turning to the deposit ratio, the less deposit-intensive banks show on average stronger reactions to monetary policy announcements. Therefore, the results underpin the view of Ricci (2015) but are inconsistent with the findings of English et al. (2018) and Ampudia and Van den Heuvel (2019).

For the three shocks, the mean coefficients of banks located in fixed-rate countries are in absolute terms and on average higher compared to banks in variable-rate countries. However, the difference in mean coefficients is only marginally significant for the monetary policy shock and insignificant for the central bank information shock and the slope surprise. This result is consistent with banks in fixed-rate counties facing higher interest rate risk compared to variable-rate countries (Hofmann et al., 2018; Ampudia and Van den Heuvel, 2019).

Country-specific differences are reported in table 2.7. The coefficients of fixed-rate countries (BE, DE, FR) are very similar. Still, French banks seem to be more exposed to central bank information shocks, while German banks are affected more from slope surprises. Concerning variable-rate countries, Greek banks are different with respect to the slope surprise. Stocks of the underlying banks in Greece have negative coefficients for the second principal component. One possible explanation is bad asset quality, such as high shares of non-performing loans, which is not included in this analysis due to data limitations.

To sum up, stocks are more sensitive to monetary policy shocks when the bank is large, operates with a lower deposit ratio, or is located in a fixed-rate country. These effects can be driven by different financing conditions, but also by fragmentation of equity markets. It has to be pointed out that one should not interpret these results causally. We do not control for correlations and dependencies in the reported bank characteristics. Moreover, there might be other bank-specific variables that influence a bank's sensitivity to monetary policy announcements. However, this exercise is helpful in studying potential drivers of bank stock responses to monetary policy announcements.

2.6 Conclusions

We aimed to shed more light on the reaction of European bank stocks to ECB announcements of monetary policy decisions by building on the considerations of Jarociński and Karadi (2020) in using high-frequency identification and sign restrictions. Consistent with the idea that the NIM is an essential driver of bank profitability, we show empirical evidence that bank stock investors value positive surprises in the yield curve after the financial crisis, especially in the low interest rate environment. Moreover, the stock prices of European banks became more sensitive to information shocks after the financial crisis. The results highlight the criticality of considering state-dependent and time-dependent variations in stock price reactions to ECB announcements. The findings extend the existing literature resolving the asset price puzzles (Jarociński and Karadi, 2020; Miranda-Agrippino and Ricco, 2021) associated with the announcement of monetary decisions. Concerning the cross-sectional heterogeneity, stocks appear to be more sensitive to shocks transmitted by ECB announcements when the bank is large, operates with a lower deposit ratio, or is located in a fixed-rate country.

As a caveat, the reasons for the time dependency of sensitivities to ECB shocks is not entirely apparent. On the one hand, the "lower-for-longer" environment could drive the higher sensitivity with bank stock investors appreciating ECB communication that signals higher long-term rates. In this sense, the reactions could be dependent on the unprecedented low levels of interest rates. On the other hand, after the experience of the financial crisis, central bank communication could also have become generally more important. In any case, and this represents a significant limitation, stock price reactions to monetary policy announcements should not be extrapolated into the future.

In the medium to long term, sufficient profitability is important for the health of banks and thus for financial stability (Altavilla et al., 2018). While accounting measures of profitability derived from banks' balance sheets are available only with a substantial time lag, stock prices reflect changes in future expected profitability in a timely manner. Hence, the influence of monetary policy announcements on the stock prices of banks may serve as an additional source of information for supervisors.

The exit from ultra-loose monetary policy gives researchers the opportunity to further understand the effects of monetary policy and information shocks on asset prices. More variation in policy rates may also help to better identify the drivers of the heterogeneity in stock price responses that we have seen throughout this paper.

2.7 Appendix

Table 2.8: Correlations of financial variables during monetary events (excluding outliers)

Pre financial crisis: January 1999 - August 2008 (144 observations)					
	OIS_1M	OIS_1Y	DE10Y	STOXX50	SX7E
OIS_1M	1				
OIS_1Y	0.3525	1			
DE10Y	0.0363	0.6317	1		
STOXX50	-0.0676	0.0397	0.0211	1	
SX7E	-0.0847	-0.0706	-0.0069	0.8945	1
Post financial crisis: September 2008 - March 2021 (116 observations)					
	OIS_1M	OIS_1Y	DE10Y	STOXX50	SX7E
OIS_1M	1				
OIS_1Y	0.5885	1			
DE10Y	0.1743	0.5657	1		
STOXX50	-0.0725	-0.0098	0.0531	1	
SX7E	-0.0115	-0.0028	0.2227	0.8451	1
Full sample: January 1999 - March 2021 (260 observations)					
	OIS_1M	OIS_1Y	DE10Y	STOXX50	SX7E
OIS_1M	1				
OIS_1Y	0.4514	1			
DE10Y	0.1007	0.5887	1		
STOXX50	-0.0686	0.0143	0.0387	1	
SX7E	-0.0327	-0.0213	0.1474	0.8199	1

Notes: The table shows the correlation of changes in the 1 month OIS rate (OIS_1M), 1 year OIS rate (OIS_1Y), 10 years German government bond rate (DE10Y), EURO STOXX 50 Index (STOXX50), and EURO STOXX Banks Index (SX7E) during windows around monetary policy events. The underlying data was taken from the Euro Area Monetary Policy event study Database (EA-MPD) which was constructed by Altavilla et al. (2019). Correlations are based on the "Monetary Event Window", in which changes are calculated from median quotes in 13:25-13:35 CET and 15:40-15:50 CET. The sample is divided into a pre financial crisis and post financial crisis subsample in September 2008 (bankruptcy of Lehman Brothers). To exclude potential outliers, data below the 1st and above the 99th percentile of each variable was dropped.

Chapter 3

EU Stock Market Correlations - An Update

Abstract

The correlation of stock markets plays a crucial role for portfolio risks through diversification effects. In addition, it can provide insights into the underlying connectedness of economies. We investigate the co-movement between the German stock market and index returns in the Czech Republic, France, Italy, Poland, Romania, and the United Kingdom during periods of elevated systemic stress. These periods include the GFC, the European SDC, the COVID-19 crisis, and the time around the beginning of the Russian invasion of Ukraine. Using the GARCH-DCC approach proposed by Engle (2002), we find substantial variation in time-varying correlations, which is especially pronounced for the CEE markets. Consistent with recent studies on the impact of COVID-19 on financial markets, we show evidence that correlations increased to unprecedented levels for some country pairs.

3.1 Motivation

The onset of the first wave of the COVID-19 pandemic in March 2020 has led to an enormous uncertainty about future economic activity, global supply chains, regional and international businesses, and social coexistence. Concerns about the spread of the virus, its contagiousness, and pathogenicity, as well as government policies to contain the spread of the virus, resulted in a dramatic deterioration of investors' sentiment and economic outlook. European and global stock markets experienced massive setbacks during the outbreak of the COVID-19 pandemic in March 2020.

Extending the extensive and growing literature on COVID-19 effects on stock market volatility, we focus explicitly on the correlation between European stock markets. The correlation of financial markets is highly relevant from different perspectives. First, from an economic perspective, variation in long-term trends of correlation can signal changes in underlying economic connectedness. A stronger co-movement might be caused by more strongly integrated real economies and/or financial markets. If companies in two areas become more integrated, e.g., if supply chains and sales markets become more aligned, then we expect effects on revenues and profits from shocks affecting these common procurement and sales markets to become more similar. Under the assumption of efficient markets, we expect elevated synchronicity in the reaction of stock prices to these shocks. Accordingly, stronger co-movement between equity indices of two areas might reflect a growing connection in businesses operating in these regions. Hence, the stock market correlation may uncover the degree to which two economic areas are integrated. Second, from an investors' perspective, correlations are crucial for steering portfolio risks in the sense of Markowitz (1952). Higher correlation between two markets limits the opportunities for portfolio risk diversification arising from investing in different regions (Cappiello et al., 2006). As a consequence, the benefits of geographical diversification are reduced as correlations between the assets increase. Therefore, correlations between financial assets in general, and stock prices in particular, constitute important metrics for risk management and financial stability considerations.

Against the background of the stock market crash related to the onset of the COVID-19 crisis, we study correlation dynamics between large Western European and smaller Central East European (CEE) stock markets. The pathway of pairwise correlations is especially interesting during market turmoils, as conditional correlations of equities among regions soar (Cappiello et al., 2006). The co-movement of selected European stock markets during the COVID-19 stock market crash is clearly visible in figure 3.1. From a longer-term perspective, European stock markets have experienced a strong increase in co-movement which is attributed to the expectation or implementation of the EA (e.g., Hardouvelis et al., 2006; Cappiello et al., 2006). We use the experience of the recent market turmoil to shed more light on the linkages between European equity markets.

Using the GARCH Dynamic Conditional Correlation (GARCH-DCC) framework of Engle (2002) we estimate correlations of stock index returns between Germany and Western European markets (France, Italy, United Kingdom) and CEE markets (Czech Republic, Poland, Romania). We compare the correlations of different crisis periods, i.e., the GFC, the SDC, the COVID-19 crisis, and the period covering the start of the Russian invasion of Ukraine.

We extend the existing literature on the COVID-19-related stock market turmoil by comparing correlations with previous (i.e., the GFC and the SDC) and subsequent crisis episodes (i.e., the start of the Russian invasion of Ukraine). Consistent with the existing literature on the COVID-19-related stock market crash, we find that equity index returns across European countries revealed strong dependence and co-movement (e.g., Zhang et al., 2020; Youssef et al., 2021). We demonstrate that crisis-related maxima in correlation with the German equity market are typically higher in the COVID-19 crisis compared to the GFC, while the reverse holds for mean correlations. Moreover, co-movements show stronger variation during the COVID-19

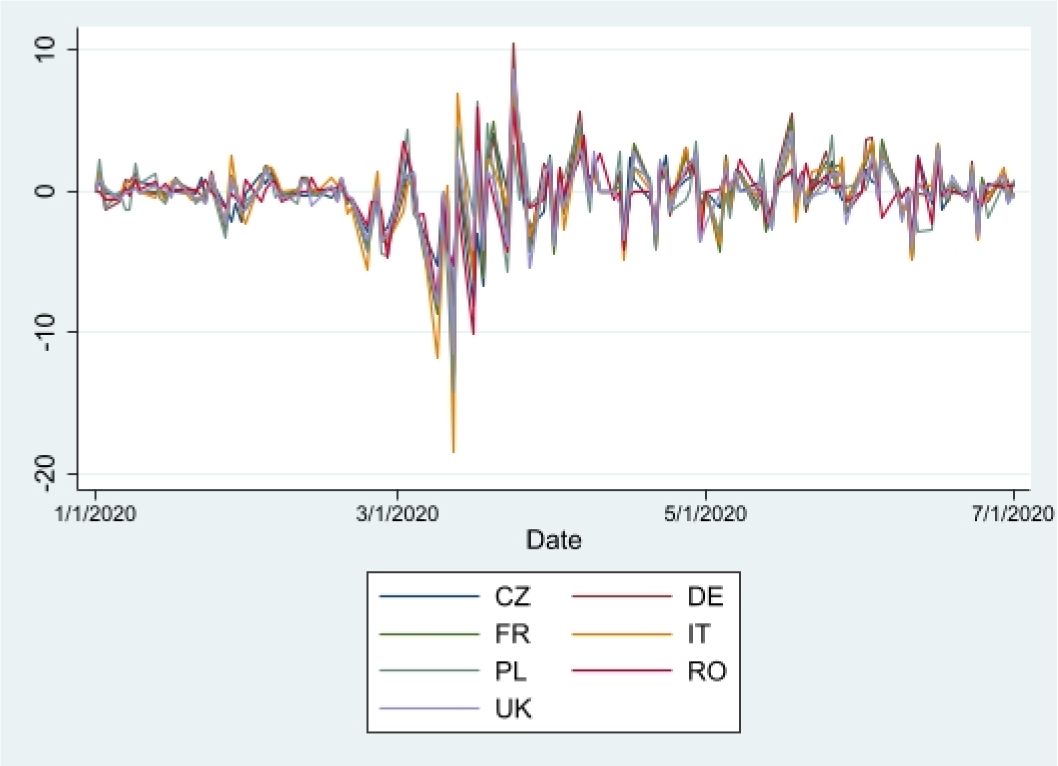


Figure 3.1: Returns of selected European stock market indices during the first half of 2020

Notes: Returns are calculated as log-differences of index levels (unadjusted for trading holidays). The index selection is explained in section 3.3. *Raw Data Source*: Refinitiv Eikon Datastream.

crisis compared to the GFC. We find evidence that systemic stress increases stock market correlations in the COVID-19 crisis, and this reaction shows heterogeneous patterns across countries. Furthermore, stronger COVID-19-related policy responses in Italy are associated with elevated correlations, which may reflect the crucial role of Italy for global financial markets during the COVID-19 crisis (Just and Echaust, 2020). As a caveat, systemic stress can only explain a relatively small share of the overall variation in correlations.

The remainder is organized as follows. Section 3.2 reviews the literature on co-movements and contagion in European stock markets with a special focus on the COVID-19 crisis. Section 3.3 describes the data for calculating DCCs. In section 3.4, the methodology for estimating correlations is explained, and subsequent analysis is carried out. Section 3.5 discusses alternative correlation measures and several limitations. Finally, section 3.6 concludes.

3.2 Literature

There is extensive literature on the long-run drivers of the correlation between European stock markets. This literature review focuses primarily on Generalized Autoregressive Conditional Heteroskedasicity (GARCH) and GARCH-DCC applications to European stock markets and studies focusing on the impact of COVID-19 on European stock markets.

Hardouvelis et al. (2006) analyze the stock market integration of 11 EA countries and the United Kingdom in the 1990s. They find that stock markets became more integrated as differentials in forward interest rates vis-à-vis Germany and inflation rates vis-à-vis the countries with the lowest inflation rates decreased. The differentials of forward interest rates to the corresponding German rates have been considered as a proxy for the probability of joining the EA (Hardouvelis et al., 2006). The increase in stock market integration seems to be driven by the expectation of future EA membership as the stock market integration of the United Kingdom has not increased (Hardouvelis et al., 2006). Cappiello et al. (2006) include data beyond 1999 and show evidence for a substantial increase in correlation since the actual implementation of the EA, with a more pronounced effect for EA countries.

With respect to the special role of the United Kingdom and the European Economic integration, Gottschalk (2021) studies weekly dynamic conditional correlations of manufacturing stocks from the early 1970s until 2019. She finds evidence that stock market correlations among the largest European economies increased from the mid-1980s on. Also informative for our study, the author investigates the relevance of global, i.e., the 1987 stock market crash and the 2008 GFC, and European shocks, i.e., the crisis of the European Exchange Rate Mechanism in 1992 and the Brexit referendum in 2016. Gottschalk (2021) finds that stock returns show higher co-movement after global shocks but lower after the occurrence of European shocks, with material consequences for risk diversification. In this context, Gottschalk (2021) shows that UK stocks of the various industrial sectors are integrated to varying degrees with their continental European counterparts.

Our sample of countries is close to the selection of Égert and Kočenda (2011) who estimate correlations based on intraday returns within a GARCH-DCC framework using equity index data from 2003-2006. Besides the large and developed markets in France, Germany, and the UK, they consider the relatively new EU markets of Hungary, the Czech Republic, and Poland. In their study, the French market serves as a benchmark for estimating dynamic conditional correlations. Overall, they find that the correlation between the German and French index is high. Both the French and the German stock market are also substantially correlated with the UK; however, correlations are typically not as high as between Germany and France. In contrast, Égert and Kočenda (2011) find rather small intraday return co-movement between the developed markets and the CEE markets. Interestingly, the correlation of intraday returns within the group of emerging markets is also weak (Égert and Kočenda, 2011).

A relatively novel strand of the literature applies Dynamic Conditional Correlation - Mixed Data Sampling (DCC-MIDAS) in order to separate short- and long-term components of stock market correlation (Mobarek et al., 2016; Virk and Javed, 2017; Niţoi and Pochea, 2019). Mobarek et al. (2016) investigate the co-movement of stocks within advanced and emerging as well as between advanced and emerging markets, using data of stock indices from 1999-2011. They empirically investigate the "wake-up call hypothesis" during the GFC and find evidence that the driving forces of co-movements within emerging markets and between emerging and developed markets are crisis-dependent, while the mechanisms do not change between the GFC-period and non-crisis times for the advanced markets (Mobarek et al., 2016). Virk and Javed (2017) examine the integration of stock markets in France, Germany, Greece, Italy, Spain, Switzerland, and the United Kingdom from 1990-2013. They find market size to be crucial for the convergence patterns as large markets show smaller short-term convergence and higher persistence in the long-term connectedness (Virk and Javed, 2017). In a similar vein, Niţoi and Pochea (2019) decompose the short- and long-term correlations of 24 EU stock market indices from 2001-2016. Typically, correlations between advanced markets are higher and show smaller volatilities compared to correlations within emerging markets (Niţoi and Pochea, 2019, p. 62). They find co-movement to depend on the level of economic development and the deepening of the markets (Niţoi and Pochea, 2019).

Cappiello et al. (2006) introduce the Asymmetric Generalized Dynamic Conditional Correlation (AG-DCC) model, which allows for conditional asymmetries in correlations of returns and find conditional correlations to be stronger influenced by bad news compared to good news. As correlation among equity markets increases due to bad news, diversification effects decrease (Cappiello et al., 2006, p. 567), having important consequences for financial stability considerations. Furthermore, the authors show that the irrevocable fixing of exchange rates related to the introduction of the EA in January 1999 has increased European stock market correlations. While the rise in correlation was stronger between France, Germany, and Italy, also the correlations between these countries and the UK have risen, however, less pronounced (Cappiello et al., 2006, p. 560-561).

Ahmad et al. (2014) focus on contagion effects of stock markets of crisis-tron countries (Greece, Ireland, Italy, Portugal, and Spain) and the US on a set of EA and non-EA markets during the SDC from 2009 to 2012. They provide evidence that DCCs increase during the crisis entailing high contagion effects, not only for EA but also for non-EA markets.

There is an extensive and fast-growing literature on global stock market reactions and contagion effects during the COVID-19 pandemic. Most of these studies focus on stock market volatility rather than correlation effects (Alan et al., 2020; Baek et al., 2020; Bakry et al., 2022; Baig et al., 2021; Albulescu, 2021; Zaremba et al., 2020). A complete literature review would by far exceed the scope of this paper. Therefore, after a brief overview of the global context, the focus will be on the pandemic-related impact on European stock markets or the impact of the European COVID-19 situation on global stock markets.

In an early study of COVID-19 effects on global equity markets, Zhang et al. (2020) demonstrate a strong increase in volatility and show that market reactions depend on the pandemic activity in the countries. Various studies find evidence for contagion effects in stock markets during the COVID-19 crisis (e.g., Liu et al., 2022; Okorie and Lin, 2021; Uddin et al., 2022). Further demonstration of contagion in international stock markets is shown in Akhtaruzzaman et al. (2021) focusing on DCCs between G7 countries and China. The rise in correlations was more emphasized for financial firms, referring to their special role in spreading contagion risks (Akhtaruzzaman et al., 2021).

The question arises as to why COVID-19 has affected the stock markets to such a large extent. Focusing on the US, Baker et al. (2020) show that COVID-19 related news had a strong impact on US equities during the first wave in early 2020, while previous pandemics such as the Spanish Flu (1918-1920) and the influenza pandemics (1957-1958 and 1968) had at most a small effect on US stock market volatility. The authors attribute these unprecedented strong reactions to business closures and restrictions within a more service-oriented economic system (Baker et al., 2020).

Despite the vast and growing body of literature on COVID-19 effects on stock markets, studies focusing explicitly on correlations of European markets are limited. Pardal et al. (2020) analyze, in particular, the integration of CEE capital markets during the COVID-19 outbreak and find evidence for substantial integration, which limits the benefit from portfolio diversification. Another study of CEE stock markets during the COVID-19 crisis, which is related to our analysis in terms of the time period and the countries considered, is Karkowska and Urjasz (2022). However, while our focus is on intra-European co-movement, Karkowska and Urjasz (2022) include the US market in their investigation. They find that linear correlations of CEE stock indices with the other markets considered are lower compared to Western European markets. Consistent with our findings, they show a strong rise in correlation in early 2020 (Karkowska and Urjasz, 2022). Youssef et al. (2021) estimate dynamic connectedness between stock markets in China, France, Germany, Italy, Russia, Spain, the UK, and the US from 2015 until March 2020 and show that total connectedness increased to unprecedented levels during the COVID-19 crisis.

In contrast, Borgioli et al. (2020) show evidence that COVID-19 increased fragmentation, and therefore decreased integration, of European financial markets. They postulate a negative relationship between systemic risk and the integration of EA financial markets. Unlike almost all other studies cited here, their integration measures are not the (dynamic) correlations between stock index returns but more complex indicators based on, inter alia, earnings returns (Kochanska et al., 2020).

Duttilo et al. (2021) find heterogeneous reactions of stock market volatilities to the COVID-19 pandemic across EA countries. Using a Threshold GARCH-in-Mean model, the authors show evidence that the first wave had a stronger effect on larger stock markets than smaller financial centers in the EA. For the majority of markets, the impact of the COVID-19 pandemic on volatility softens as the second wave is in most cases not significant (Duttilo et al., 2021).

There is also evidence that the spread of the virus in Italy was a crucial factor in the deterioration of investor sentiment, as shown in Just and Echaust (2020). They find that new COVID-19 cases in Italy have increased implied volatility and implied correlation of the US stock market (Just and Echaust, 2020, p. 5). These findings are partly supported by Onali (2020).[1]

[1]The VAR results in Onali (2020) imply that the number of deaths in Italy and France had a positive impact on the volatility index and a negative effect on equity returns in the US. However, GARCH results, except for China, do not show a significant influence of reported cases and fatalities on US returns (Onali, 2020).

3.3 Data

We calculate index returns based on daily closing values of stock market indices. For larger Western European stock markets, we select the CAC40 (France), the FTSE MIB (Italy), the FTSE 100 (United Kingdom) in addition to the DAX (Germany). For the CEE markets, we choose the PX 50 (Czech Republic), the WIG 20 (Poland), and the BET (Romania). All index levels are retrieved from Refinitiv Eikon Datastream. Our initial sample covers the period from December 31, 1999, until June 30, 2022. We calculate the returns r_t based on the log difference of index values S_t, i.e.,

$$r_t = [ln(S_t) - ln(S_{t-1})] * 100. \tag{3.1}$$

As elucidated by Jondeau and Rockinger (2006), the occurrence of trading holidays may lead to spurious correlations. If exchanges are closed, stock indices of these countries show zero returns on the respective days. As these zero returns are not driven by fundamental market forces but institutional settings, holidays may distort correlation estimates. To avoid problems arising from stale prices and trading holidays, we calculate the index returns as follows: We drop observations when at least one of the indices has a zero return, i.e., when it exhibits exactly the same value as on the previous observation. In the next step, we re-calculate the returns as shown in equation 3.1. Finally, we subtract the respective sample mean of each time series from the return observation to obtain a zero mean time series as in Engle (2002). This procedure ensures a synchronous dataset in which all returns of a specific trading day are based on the same information set, i.e., accumulated returns for countries with open exchanges when other countries have a trading holiday.

Summary statistics for the selected stock market indices are presented in table 3.1. The distribution of demeaned returns is negatively skewed and leptokurtic, which is also reported for other asset price returns (Mandelbrot, 1997, p. 372). Variance, skewness, and kurtosis of the selected index returns show considerable variation, however, without a noticeable difference between Western and Eastern European markets. The results of the Dickey and Fuller (1979) test (table 3.2) imply that the assumption of stationary is appropriate as we can reject the null hypothesis that the demeaned series follow a unit-root process.

Table 3.1: Summary statistics of returns

VARIABLES	N	SD	Var	Skewness	Kurtosis
CZ	5,287	1.367	1.869	-0.511	15.98
DE	5,287	1.519	2.308	-0.150	8.582
FR	5,287	1.488	2.215	-0.172	9.291
IT	5,287	1.584	2.510	-0.627	11.36
PL	5,287	1.560	2.434	-0.257	7.629
RO	5,287	1.535	2.356	-0.436	13.00
UK	5,287	1.227	1.504	-0.234	10.94

Notes: The underlying returns are demeaned and prepared as described in section 3.3. The observations cover the time period from January 2000 to June 2022.

Table 3.2: Dickey-Fuller test

Country Index	CZ	DE	FR	IT	PL	RO	UK
Test statistic	-68.76	-73.70	-75.26	-75.51	-71.27	-66.46	-75.64
1% critical value	-3.43	-3.43	-3.43	-3.43	-3.43	-3.43	-3.43
MacKinnon approximate p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	5286	5286	5286	5286	5286	5286	5286

Notes: The table shows results of the Dickey and Fuller (1979) test with corresponding p-values according to the method of MacKinnon (1994). The underlying returns are demeaned and prepared as described in section 3.3. The observations cover the time period from January 2000 to June 2022.

In our subsequent analysis, we estimate conditional correlations where the German market serves as the benchmark, since Germany is the largest economy in the EA and the EU.

3.4 Estimation

3.4.1 Estimation of DCCs

Correlations are estimated by applying the GARCH-DCC model proposed by Engle (2002) and Aielli (2013) to the return data.

As described in section 3.3, the corresponding time series average μ of each return series was subtracted from the return observations to obtain demeaned returns, i.e.,

$$r_t^* = r_t - \mu. \tag{3.2}$$

As outlined in Engle (2002) and Aielli (2013), the conditional covariance matrix H_t can be expressed as a product of the diagonal matrix of conditional variances D_t and the conditional correlation matrix R_t, i.e., the conditional covariance matrix of standardized residuals[2],

$$H_t = D_t^{1/2} R_t D_t^{1/2}, \tag{3.3}$$

with

$$R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2}. \tag{3.4}$$

The dynamics of correlations can be described by

$$Q_t = S(1 - \alpha - \beta) + \alpha(\epsilon_{t-1}\epsilon'_{t-1}) + \beta Q_{t-1}, \tag{3.5}$$

where S is the unconditional correlation matrix of standardized residuals $\epsilon_t = r_t^*/\sqrt{h_t}$ and α, β are parameters steering the correlation process based on past shocks and past conditional correlation (Engle, 2002; Gottschalk, 2021).

[2]Please note that in the original works of Bollerslev (1990) and Engle (2002), D_t denotes the diagonal matrix of standard deviations. In contrast to the time-invariant matrix in Bollerslev (1990), the correlation matrix in Engle (2002) varies over time.

The estimates for the ARCH and GARCH parameters are depicted in table 3.3 (estimated in STATA). Consistent with the findings in Engle (2002, p. 349) and Gottschalk (2021, p. 15), the parameter related to past shocks α is relatively small for all countries, while the second parameter β is well above 0.9 in all cases. This implies a high persistence in correlations, i.e., past correlations highly influence correlations today. For brevity, we will not further discuss the ARCH- and GARCH-terms as we are primarily interested in conditional correlations.

We estimate the DCCs for the entire continuous time series using over 5,000 observations.[3] In our subsequent analysis, we compare the evolution of conditional correlations during four major crises or periods of high volatility, the GFC, the SDC, the COVID-19 crisis, and the period containing the start of the Russian invasion of Ukraine in 2022. These periods are marked by a substantial rise in systemic stress, measured by the ECB Composite Indicator of Systemic Stress (CISS) for the EA, as shown in figure 3.2. The CISS is a measure of the stress level in the financial system. The composite index is constructed from five different subindices, measuring stress in the money market, the bond market, the equity market, the financial intermediary sector, and the currency market. Each subindex comprises up to three raw indicators, mainly realized volatilities and spreads (Holló et al., 2012). Time-dependent correlations between these subindices are taken into account when aggregating the five subindices into the composite index.[4] For the preliminary visual inspection of dynamic correlations, we define a period beginning one year before the peak of the crisis (or the pivotal event) until one year after. As the main event for the GFC we choose September 15, 2008, when Lehman Brothers filed for bankruptcy (Fender and Gyntelberg, 2008). For the SDC, the choice of a central event is less

[3]At the beginning of the sample, DCCs seem to be unreasonably low. This pattern is observed frequently in relevant user forums. However, DCCs converge very soon to appropriate levels which can be checked by comparing DCCs to (simple) rolling-window correlations (see section 3.5). Hence, the initial difference in correlations should not impact our results, as there is a sufficient time lag between the start of the DCC estimation and the beginning of our first period of interest, the GFC.

[4]For further methodological details see Holló et al. (2012). The CISS data was retrieved from the ECB's statistical data warehouse.

evident. We choose November 2011 as the center of the crisis since the systemic stress indicator shows a peak. Previous findings in the literature on systemic risks in the banking sector related to sovereign risk support our selection, e.g., Black et al. (2016). Inspired by Zhang et al. (2020), we select March 11, 2020, as the pivotal date related to the COVID-19 crisis when the WHO characterized the disease as a pandemic (WHO, 2020). We finally compare the correlations during the GFC and the COVID-19 crisis with the very recent episode covering the start of the Russian invasion on Ukraine on February 24, 2022, and the subsequent rise in inflation rates (European Council, 2022). The last period, i.e., the period marked by the Russian invasion of Ukraine covers only one year (June 30, 2021 - June 30, 2022) to avoid an overlap with the COVID-19 episode. The classification does not claim to cover all events of the underlying crisis, nor that movements in the financial markets are entirely attributable to the crisis in question. Rather, the aim is to compare periods of equal length (two years with the exception of the last crisis) that include the main event or the most turbulent point in time within that crisis.

Table 3.3: GARCH-DCC results

EQUATION	VARIABLES	(1) CZ	(2) FR	(3) IT	(4) PL	(5) RO	(6) UK
ARCH_r_DE	L.arch	0.0767***	0.0834***	0.0749***	0.0798***	0.0829***	0.0774***
		(0.00618)	(0.00486)	(0.00469)	(0.00631)	(0.00692)	(0.00511)
	L.garch	0.910***	0.907***	0.919***	0.909***	0.904***	0.910***
		(0.00702)	(0.00526)	(0.00503)	(0.00703)	(0.00777)	(0.00586)
	Constant	0.0274***	0.0262***	0.0193***	0.0266***	0.0283***	0.0268***
		(0.00417)	(0.00328)	(0.00291)	(0.00414)	(0.00454)	(0.00365)
ARCH_r	L.arch	0.110***	0.0936***	0.0848***	0.0568***	0.191***	0.0861***
		(0.00821)	(0.00583)	(0.00541)	(0.00440)	(0.0147)	(0.00637)
	L.garch	0.873***	0.897***	0.912***	0.934***	0.808***	0.899***
		(0.00887)	(0.00630)	(0.00546)	(0.00506)	(0.0125)	(0.00757)
	Constant	0.0328***	0.0288***	0.0182***	0.0238***	0.0496***	0.0209***
		(0.00461)	(0.00365)	(0.00294)	(0.00433)	(0.00642)	(0.00292)
Adjustment	α	0.0189***	0.0457***	0.0496***	0.0151***	0.0190***	0.0464***
		(0.00300)	(0.00335)	(0.00470)	(0.00235)	(0.00296)	(0.00443)
	β	0.972***	0.933***	0.928***	0.979***	0.972***	0.932***
		(0.00472)	(0.00472)	(0.00765)	(0.00333)	(0.00483)	(0.00706)
SINGLE	/corr(r_DE,r)	0.535***					
		(0.0291)					
	/corr(r_DE,r)		0.932***				
			(0.00527)				
	/corr(r_DE,r)			0.858***			
				(0.0108)			
	/corr(r_DE,r)				0.603***		
					(0.0327)		
	/corr(r_DE,r)					0.306***	
						(0.0383)	
	/corr(r_DE,r)						0.840***
							(0.0120)
	Observations	5,287	5,287	5,287	5,287	5,287	5,287

Notes: The table shows the results of the GARCH-DCC estimation. All models were estimated without a constant since the return-data was demeaned. The first group of rows report the results of the variance equation for the German market. The second group of rows report the results of the variance equation for the respective country index. α and β are the GARCH-DCC adjustment parameters. The conditional quasicorrelations and the number of observations are reported below. The estimation covers the period from January 2000 until June 2022. Significance levels: *** 1%, ** 5%, * 10%.

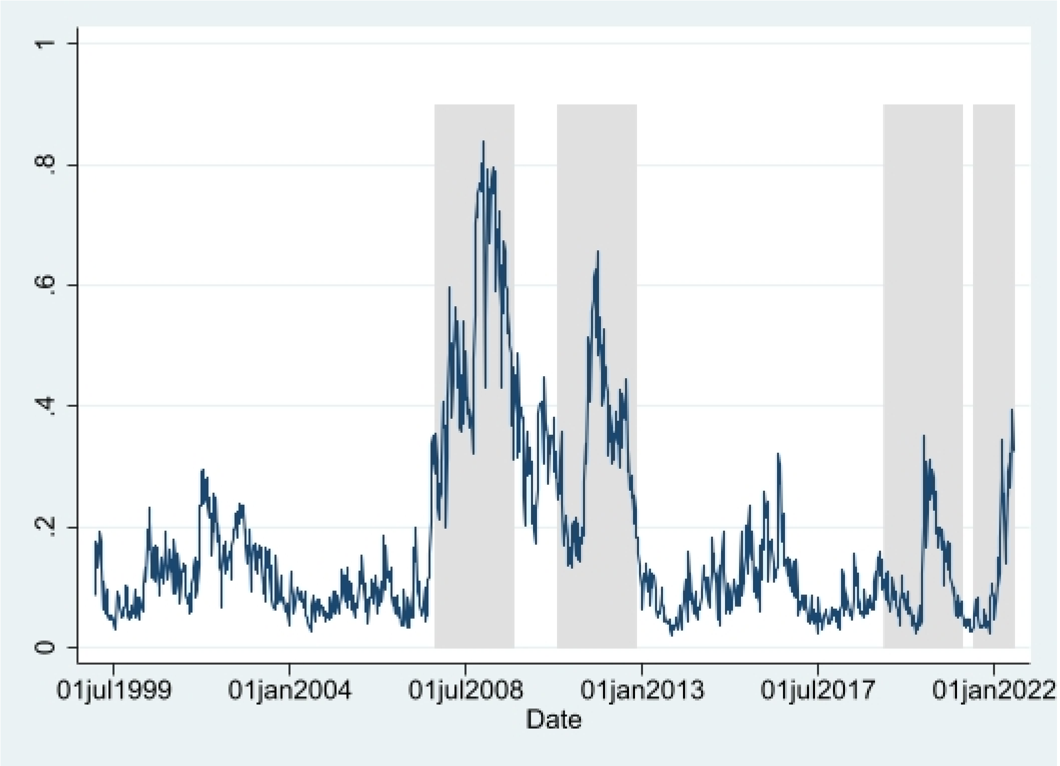


Figure 3.2: EA Composite Indicator of Systemic Stress

Data Source: ECB. Data as of August 2022.

Figure 3.3 shows the predicted dynamic conditional correlations of the stock market in Germany with France (CAC40), Czech Republic (PX 50), Italy (FTSE MIB), Poland (WIG 20), Romania (BET), and the United Kingdom (FTSE 100). The samples are divided into the GFC, the European SDC, the COVID-19 crisis, and the period containing the Russian invasion of Ukraine, as described above. Around the bankruptcy of Lehman Brothers on September 15, 2008, conditional correlations with the German stock market increased only moderately for Italy and the United Kingdom. The correlation prediction for the country pair France and Germany does not reveal any substantial variation. Correlations with CEE markets (CZ, PL, RO) show a more pronounced increase, especially for Romania, which is less correlated with the German market. The co-movement between the German and the CEE stock markets weakened in early 2009.

In the period covering the peak of the SDC, correlations between the German market and CEE stock market indices increase until late 2011 and then stagnate or decrease moderately. DCCs between German and Polish stocks seem to be consistently higher than German-Czech DCCs during a prolonged period.

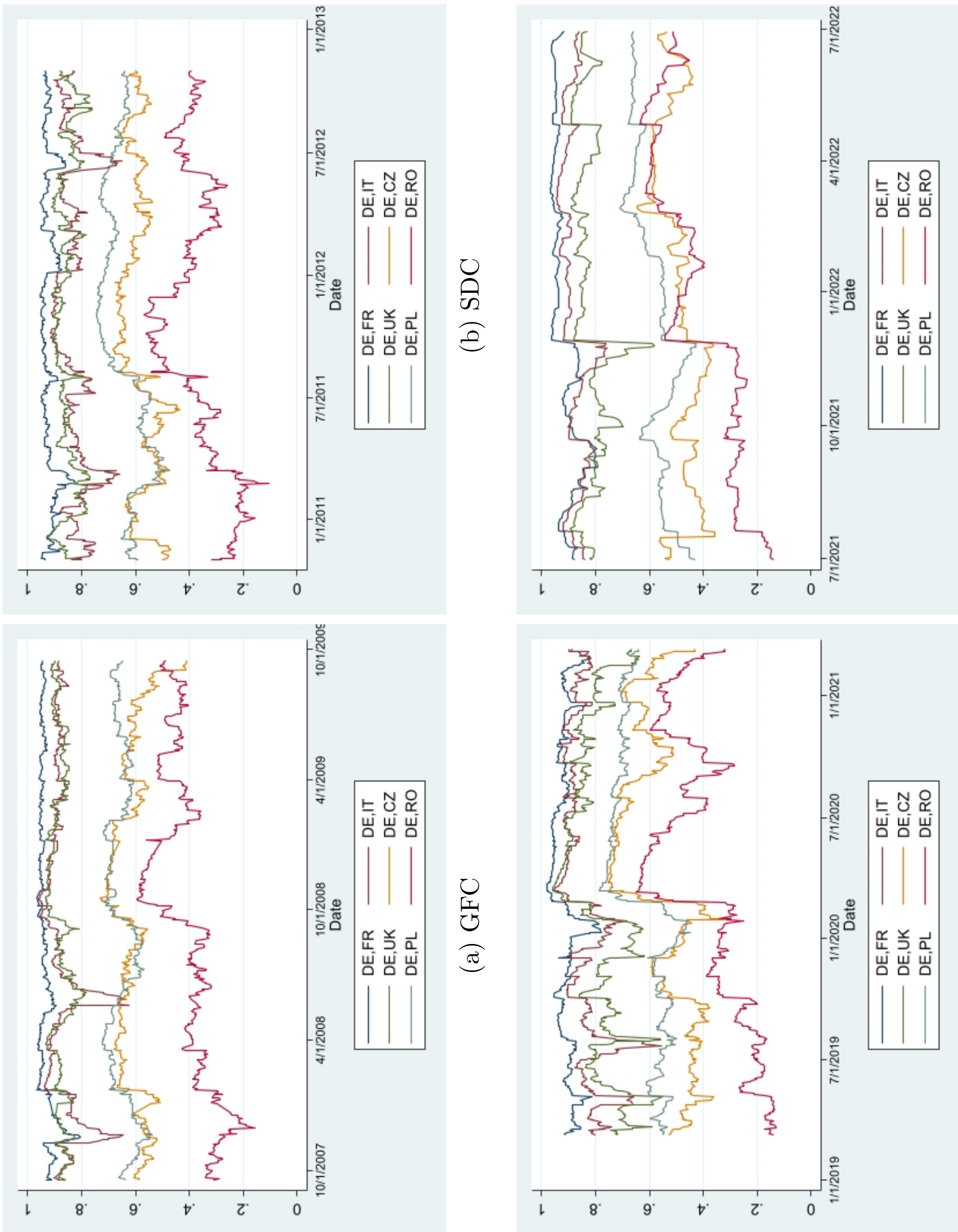
During the COVID-19 stock market turmoil, the variations of dynamic conditional correlations were soaring at the end of February 2020 and further rising in March (see figure 3.3c). The variation in dynamic conditional correlation was higher during the COVID-19 period compared to the GFC and more perceptible, especially for the Western European markets. Again, the correlations between the German and the CEE stock markets are lower than between Germany and other Western European countries. Generally, French and German stocks show the strongest co-movement, followed by the group containing Italy and the United Kingdom. The dynamic correlations with Poland and the Czech Republic are well below the level of the EA markets. As during the previous crisis episodes, the smallest co-movement within the sample exists between German and Romanian stocks.

The period containing the beginning of the Russian war in Ukraine is marked by several jumps in correlation as depicted in figure 3.3d. The strong increase in DCCs in November 2021 resulted from large drops in the underlying stock market indices. Fears related to a new coronavirus variant led to large negative returns of global stock market indices on November 26, 2021 (Gregg, 2021). Interestingly, for some countries, the surge in correlation is stronger and sharper compared to the GFC. As a result of the Russian invasion of Ukraine on February 24, 2022, the rise in DCCs is clearly visible for CEE countries. However, correlations have already been at a high level, so the increase in co-movement was limited. A further increase in correlations, also for Western European markets, is clearly visible in April 2022. This month was marked by high losses in the US equity market, triggered by inflation, higher interest rate expectations, and supply chain disruptions related to the lockdown in China and the Russian war in Ukraine (Marcos, 2022).

The dynamic conditional correlations of stock market returns in the Czech

Republic (FR-CZ), Italy (FR-IT), Poland (FR-PL), Romania (FR-RO), and the United Kingdom (FR-UK) with the French stock market (CAC 40) show very similar patterns as correlations with the German market (see figure 3.4). We estimate simple correlation coefficients between dynamic conditional correlations of the five stock markets with Germany and France, taking into account the entire period from the start of the GFC sample in September 2007 until the end of June 2022. As expected, the co-movement of the considered indices with the German index is highly correlated with the co-movement with the French stock market index. This finding is not surprising as the French index is highly correlated with the German stock market (e.g., Égert and Kočenda, 2011). The correlation of dynamic conditional correlations with Germany and France is slightly higher for CEE markets (CZ: 0.96, PL: 0.95, RO: 0.97) than for Western European markets (IT: 0.87, UK: 0.90). These results ensure that the choice of the German index as the benchmark should not produce significantly different results than when the country-specific indices are correlated against the French benchmark index.

When comparing summary statistics of DCCs during the different crisis episodes, some interesting patterns emerge. First, as shown in table 3.4, for most countries, the average co-movement was highest during the period covering the bankruptcy of Lehman Brothers in 2008. Second, for all pairwise DCCs except Germany-Italy, the highest correlation within these four crisis episodes occurred during the COVID-19 period. These results imply that COVID-19 had substantial contagion effects for intra-European dependencies which expands and supports the findings of the existing literature, e.g., as in Akhtaruzzaman et al. (2021), Okorie and Lin (2021), Zhang et al. (2020). Third, co-movements measured by DCCs show higher variation during the sample containing the COVID-19 pandemic. Standard deviations of DCCs between the German and CEE indices are typically higher, and maxima are further away from their mean values. Given the findings in Gottschalk (2021), who found that Brexit has led to a divergence in returns between the UK and continental Europe, it is interesting that DE-UK DCC is on average above DE-IT DCC in the crises which occurred before the Brexit referendum in 2016, and below afterwards. While we cannot rule out that these developments are driven by different shock transmissions which are not necessarily related to the decision to leave the EU, these findings give at least further indication of a Brexit-related decrease in correlations as found in Gottschalk (2021). Mean DCCs of returns between the German market and the markets in France, Italy, and the UK are at higher levels than DCCs between Germany and CEE countries. On average, the French-German correlation exceeds all other correlations, which is in line with previous investigations (Virk and Javed, 2017; Égert and Kočenda, 2011). In all periods, the weakest link is with the Romanian market.



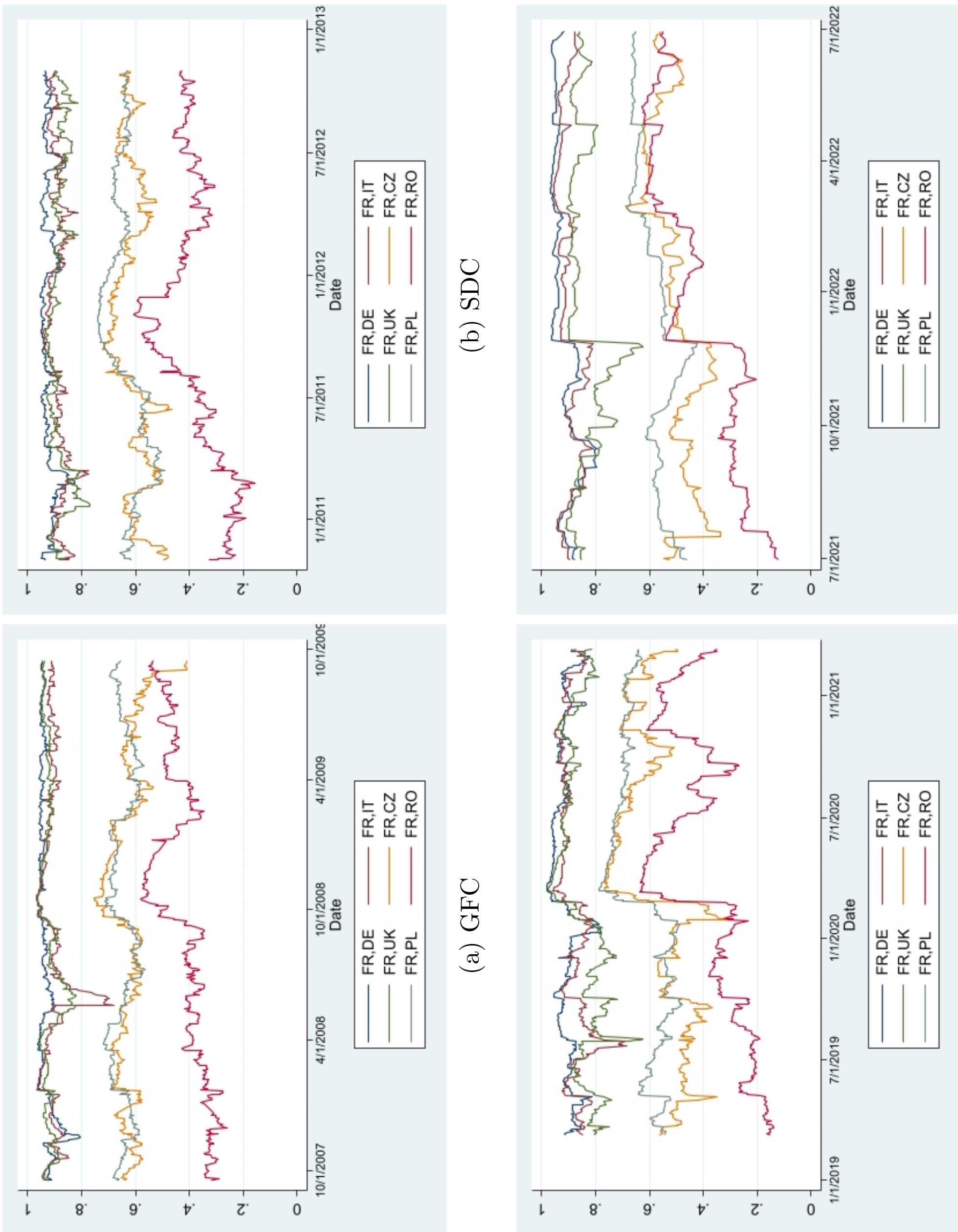
(a) GFC

(b) SDC

(c) COVID-19

(d) Ukraine

Figure 3.3: Dynamic conditional correlations, German stock index



(a) GFC

(b) SDC

(c) COVID-19

(d) Ukraine

Figure 3.4: Dynamic conditional correlations, French stock index

Table 3.4: DCC - summary statistics

	GFC			SDC			COVID-19			Ukraine		
VARIABLES	Mean	SD	Max	Mean	SD	Max	Mean	SD	Max	Mean	SD	Max
DE,FR	**0.938**	0.024	0.965	0.921	0.025	0.956	0.912	0.037	**0.981**	0.919	**0.043**	0.966
DE,IT	0.879	0.055	**0.959**	0.832	0.054	0.914	0.852	**0.062**	0.957	**0.885**	0.040	0.946
DE,UK	**0.881**	0.031	0.934	0.854	0.037	0.925	0.798	**0.087**	**0.961**	0.826	0.052	0.894
DE,CZ	**0.617**	0.058	0.729	0.587	0.055	0.683	0.562	**0.115**	**0.752**	0.490	0.067	0.646
DE,PL	**0.650**	0.043	0.723	0.649	0.066	0.746	0.635	**0.088**	**0.786**	0.588	0.068	0.710
DE,RO	0.408	0.088	0.594	0.368	0.098	0.568	0.385	**0.149**	**0.651**	**0.416**	0.141	0.635

Notes: The table shows mean, standard deviation (SD) and maximum (Max) of DCCs within the considered periods. The subsamples are defined as follows: Global Financial Crisis (GFC) 15 September 2007 - 15 September 2009, Sovereign Debt Crisis (SDC) 1 November 2010 - 1 November 2012, COVID-19 11 March 2019 - 11 March 2021, and the period containing the Russian invasion of Ukraine, 30 June 2021 - 30 June 2022. For a given correlation, the maximum value of mean, SD, and Max for all four periods is reported in bold.

3.4.2 Analysis of DCCs

To investigate the variation of correlations during the four periods, we regress the DCCs on systemic stress and distinguish between stress originating from the US and the EA. We use the ECB CISS data for the US and the EA to account for overall systemic stress in these regions. Given the prominent role of the US in global financial markets, the US CISS may also be considered a proxy for the overall level of global systemic stress. Since the data on systemic stress is of weekly frequency, we assign calendar weeks to all observations and aggregate the DCC data to weekly frequency using the mean of daily DCCs within the respective calendar week.

The financial stress indicators for the EA and the US are highly correlated for the available data (R=0.84, N=1,160), which may cause a multicollinearity problem when including both indices into one regression equation. Hence, we construct an additional index, which measures the EA excess stress, i.e.,

$$CISS_s^{EA\,excess} = CISS_s^{EA} - CISS_s^{US}. \tag{3.6}$$

Consequently, $CISS_s^{EA\,excess}$ is a measure of the difference between systemic stress in the EA and the US. The correlation between the new measure $CISS_s^{EA\,excess}$ and US systemic stress is substantially lower (R=0.08, N=1,160), which makes a multicollinearity problem unlikely.

To estimate the relationship between the DCCs and systemic stress in the US and EA, we run OLS regressions separately for each country pair and crisis period, i.e., the GFC, the SDC, the COVID-19 pandemic, and the period containing the beginning of the Russian war in Ukraine. The underlying idea is that coefficients should be not systematically different from zero if correlations are independent from systemic stress. If correlation is only driven by overall systemic stress (proxied by US CISS) the coefficient of EA excess stress should not be significantly different from zero. Since the stress indicator does not appear to be stationary in some sub-periods, the first difference of the dependent and independent variables is used, i.e.,

$$\begin{aligned}\Delta DCC_{DE,i,s} &= \beta_{i,1}\Delta CISS_s^{US} + \beta_{i,2}\Delta CISS_s^{EA\,excess} + \epsilon_{i,s},\\ &= \beta_{i,1}\Delta CISS_s^{US} + \beta_{i,2}\Delta(CISS_s^{EA} - CISS_s^{US}) + \epsilon_{i,s},\end{aligned} \tag{3.7}$$

where $DCC_{DE,i,s}$ denotes the mean DCC between the German index and the stock index of country i with $i = \{CZ, FR, IT, PL, RO, UK\}$ in calender week s. The parameters $\beta_{i,1}$ and $\beta_{i,2}$ serve as sensitivities of DCCs to US and European systemic stress. Under the assumption that the DCCs are independent from overall systemic stress in the EA and the US, we would expect that estimates for $\beta_{i,1}$ and $\beta_{i,2}$ are not statistically different from zero.

Table 3.5 shows the results of the OLS regression based on the first differences. All significant coefficients are positive, which implies a positive relationship between systemic stress in the financial system and the DCCs. During the GFC we do not find evidence that DCCs between Germany and France, Italy, the United Kingdom, the Czech Republic, Poland, and Romania reacted significantly to changes in US systemic stress or excess systemic stress in the EA. This is surprising as most country pairs had higher average DCCs compared to the three other crisis periods. The variation in conditional correlation observed in figure 3.3a cannot be attributed to overall systemic stress in the financial system. For the SDC, the coefficient of excess EA systemic stress is (marginally) significant for the correlations between Germany and France, Italy, the Czech Republic, and Romania. The US CISS is insignificant except for the German-Romanian correlation. Coefficients on US systemic stress are for all country pairs consistently higher in the COVID-19 period, compared to the GFC and SDC. The difference between EA and US systemic stress is associated with significantly higher (at least at the 10% level) DCCs for Italy, the UK, Poland, and Romania. From the cross-country perspective, the positive relationship between

US systemic stress is more pronounced for DCCs of the German market with less developed markets (CZ, PL, RO). The stronger impact of overall systemic stress may explain the relatively high variation compared to Western European markets, as shown in figure 3.3c and table 3.4. Compared to the three previous crises, the correlation between Germany and France shows the highest reactions to US and EA systemic stress in the last period, from July 2021 until June 2022. During this period, excess stress in the EA is also associated with a higher correlation between Germany and Italy as well as Germany and Poland. Overall the explanatory power of the estimated models is rather low, however, alternating across periods.

To shed further light on the developments of DCCs during the COVID-19 period, we test if country-specific restrictions adopted to combat the spread of the virus had an influence on the stock market correlations. We take the COVID-19 Stringency Index, which is a part of the Oxford COVID-19 Government Response Tracker (OxCGRT) panel dataset as a proxy for national containment policies.[5]

The Stringency index aggregates data from nine ordinal sub-indicators, namely, *school closing*, *workplace closing*, *cancel public events*, *restrictions on gathering size*, *close public transport*, *stay-at-home requirements*, *restrictions on internal movement*, *restrictions on international travel*, and *public information campaign* (Hale et al., 2021, p. 530). The daily time series vary between 0 and 100 and start on January 1, 2020.

During the initial introduction of restrictions in early 2020, containment measures were more homogeneous than the local spread of the virus. In most countries, government measures put in place to hinder the pandemic activity increased substantially within a 14-day period during mid-March 2020. Later, governments' responses became more heterogeneous as the pandemic progressed (Hale et al., 2021).

The synchronicity in government responses to the COVID-19 pandemic in early

[5]The Oxford COVID-19 Government Response Tracker dataset was downloaded from `https://github.com/OxCGRT/covid-policy-tracker`.

Table 3.5: OLS Regression (differences)

	GFC	SDC	COVID19	Ukraine
DE,FR				
D.CISS_US	0.0095	0.0411	0.0964**	0.1263**
	(0.0149)	(0.0375)	(0.0412)	(0.0580)
D.CISS_EA_excess	0.0069	0.0610*	0.0346	0.1063*
	(0.0148)	(0.0317)	(0.0322)	(0.0574)
Observations	102	104	104	53
R-squared	0.0026	0.0446	0.0595	0.0511
Prob >F	0.8147	0.0841	0.0567	0.0306
DE,IT				
D.CISS_US	0.0297	0.0122	0.2114***	0.1124
	(0.0351)	(0.0831)	(0.0793)	(0.0773)
D.CISS_EA_excess	-0.0201	0.1431**	0.1426**	0.2119**
	(0.0373)	(0.0590)	(0.0651)	(0.0929)
Observations	102	104	104	53
R-squared	0.0131	0.0513	0.0520	0.0596
Prob >F	0.1982	0.0570	0.0300	0.0455
DE,UK				
D.CISS_US	0.0308	0.0496	0.2042**	0.0608
	(0.0195)	(0.0664)	(0.0934)	(0.1880)
D.CISS_EA_excess	0.0029	0.0417	0.1640*	0.2551
	(0.0181)	(0.0539)	(0.0837)	(0.1714)
Observations	102	104	104	53
R-squared	0.0235	0.0139	0.0318	0.0311
Prob >F	0.2279	0.5367	0.0723	0.3109
DE,CZ				
D.CISS_US	0.0141	-0.0996	0.2570*	0.1798
	(0.0278)	(0.0745)	(0.1344)	(0.1459)
D.CISS_EA_excess	0.0482	0.1608**	0.1355	0.1419
	(0.0312)	(0.0648)	(0.0840)	(0.1230)
Observations	102	104	104	53
R-squared	0.0217	0.1270	0.1043	0.0381
Prob >F	0.3008	0.0223	0.1450	0.3813
DE,PL				
D.CISS_US	0.0192	-0.0163	0.2159***	0.1595**
	(0.0196)	(0.0377)	(0.0784)	(0.0773)
D.CISS_EA_excess	0.0248	0.0718	0.0893*	0.2041**
	(0.0198)	(0.0445)	(0.0505)	(0.0858)
Observations	102	104	104	53
R-squared	0.0154	0.0569	0.1981	0.0814
Prob >F	0.4311	0.2737	0.0251	0.0239
DE,RO				
D.CISS_US	0.0225	0.1027*	0.3871***	0.1806
	(0.0339)	(0.0610)	(0.1455)	(0.1455)
D.CISS_EA_excess	0.0342	0.2167***	0.2579***	0.2169
	(0.0325)	(0.0749)	(0.0975)	(0.1748)
Observations	102	104	104	53
R-squared	0.0089	0.1190	0.1604	0.0331
Prob >F	0.5615	0.0051	0.0169	0.3184

Notes: The table shows OLS coefficients and the corresponding robust standard errors. The data was aggregated to a weekly frequency. The dependent variable is the DCC (first difference) between the index returns of the respective country and Germany. CISS denotes the Composite Indicator of Systemic Stress. The indicators are transformed as described in the text. The subsamples are defined as follows: Global Financial Crisis (GFC) 15 September 2007 - 15 September 2009, Sovereign Debt Crisis (SDC) 1 November 2010 - 1 November 2012, COVID-19 11 March 2019 - 11 March 2021, and the period containing the Russian invasion of Ukraine, 30 June 2021 - 30 June 2022. Significance levels: *** 1%, ** 5%, * 10%.

2020 is of great importance for our analysis as we investigate time-varying correlations of stock index returns, which can be understood as a measure of synchronicity. Thus, a relatively similar timing of the introduction of measures in various jurisdictions may have resulted in additional co-movement in the stock markets of these countries.

The OxCGRT Stringency index was already used in studies on stock market reactions to the COVID-19 pandemic. Research examining the link between stock market volatility and stringency provides partially conflicting evidence. Alan et al. (2020) find that stricter containment measures decrease stock market volatility in the cross-sectional dimension when controlling for active cases and curvature, i.e., a measure for the acceleration of the spread of the virus. In contrast, Zaremba et al. (2020) find that stringency increases equity volatility. These findings are supported by Baig et al. (2021), who show evidence for a positive impact of the OxCGRT Stringency index on the volatility of US stocks. Bakry et al. (2022) find a positive impact of the Stringency index on GARCH-volatility in emerging markets, but a negative influence on volatility in developed markets.

For our analysis, we use the OxCGRT Stringency indices of the considered countries in addition to the US CISS, which serves as a proxy for global systemic stress (equation 3.8). In addition to the corresponding country-specific Stringency indices, we control for the policy stringency in Italy, as previous literature found a special role of Italy in the transmission of the COVID-19 crisis into financial markets (Just and Echaust, 2020), i.e.,

$$\Delta DCC_{DE,i,s} = \beta_{i,1}\Delta CISS_s^{US} + \gamma_{i,1}\Delta SI_{DE,s} + \gamma_{i,2}\Delta SI_{i,s} + \gamma_{i,3}\Delta SI_{IT,s} + \epsilon_{i,s}, \quad (3.8)$$

with $i = \{CZ, FR, IT, PL, RO, UK\}$ and $SI_{i,s}$ denotes the mean Stringency index of country i in calendar week s.

In a second set of regressions, we also include the excess systemic stress in the

EA as described above,

$$\begin{aligned}\Delta DCC_{DE,i,s} =& \beta_{i,1}\Delta CISS_s^{US} + \beta_{i,2}\Delta CISS_s^{EA\,excess} \\ & + \gamma_{i,1}\Delta SI_{DE,s} + \gamma_{i,2}\Delta SI_{i,s} + \gamma_{i,3}\Delta SI_{IT,s} + \epsilon_{i,s}.\end{aligned} \tag{3.9}$$

This analysis helps to investigate further the transmission channels of shocks that led to an unprecedented level of DCC for some country pairs during the onset of the COVID-19 crisis. Given the limited number of observations for each DCC time series, we rely on the Stringency index as a comparable measure of national policies. However, this comes at the cost that the relationship between the Stringency index and the dynamic correlation may also be due to a rather indirect effect, i.e., harsher measures are imposed as a consequence of a higher number of infections and/or fatalities. Put differently, we should interpret the relationship as an aggregate COVID-19 effect stemming from policy measures which may also be driven by the virus activity, development of cases, and COVID-19-related fatalities in these jurisdictions.

As shown in tables 3.6 and 3.7, the composite stress indicators lose their significance for explaining correlations between the German stock market and the developed markets in France, Italy, and the United Kingdom, when controlling for the differenced Stringency indices. Please note that the number of observations shrinks in comparison to table 3.5 since Stringency indices are only available since 2020. The coefficients of the country-specific Stringency indices are not significant, with the exception of Italy. Overall, the explanatory power of these models is higher compared to the regressions in table 3.5. The strength of restrictions in Italy is positively related to the DCCs and statistically significant, except for the Czech Republic when controlling for excess systemic stress in the EA (table 3.7).

The size of the coefficient of the Italian Stringency index is significant and

Table 3.6: COVID-19 (differences)

VARIABLES	FR	IT	UK	CZ	PL	RO
D.CISS_US	0.0232	0.0344	0.0634	0.0806	0.0763**	0.123*
	(0.0275)	(0.0427)	(0.0506)	(0.0582)	(0.0364)	(0.0711)
D.SI_DE	-0.000563	-0.000384	-0.000936	0.00146*	0.000231	0.000613
	(0.000491)	(0.000398)	(0.00106)	(0.000778)	(0.000504)	(0.000955)
D.SI_FR	0.000350					
	(0.000310)					
D.SI_IT	0.000897**	0.00143*	0.00163*	0.00204*	0.00189***	0.00243*
	(0.000404)	(0.000793)	(0.000871)	(0.00120)	(0.000638)	(0.00121)
D.SI_UK			0.000567			
			(0.000658)			
D.SI_CZ				-0.000200		
				(0.000757)		
D.SI_PL					-4.82e-05	
					(0.000403)	
D.SI_RO						0.000546
						(0.000526)
Observations	58	58	58	58	58	58
R-squared	0.188	0.207	0.141	0.331	0.539	0.343
Prob >F	0.0127	0.0819	0.0658	0.0064	0.0004	0.0067

Notes: The table shows OLS coefficients and the corresponding robust standard errors. The data was aggregated to a weekly frequency. The dependent variable is the DCC between the index returns of the respective country and Germany. CISS denotes the Composite Indicator of Systemic Stress and SI the OxCGRT Stringency Index. The indicators are transformed as described in the text. The underlying period for the subsample is 31 January 2020 - 11 March 2021. Significance levels: *** 1%, ** 5%, * 10%.

Table 3.7: COVID-19 (differences, including CISS EA)

VARIABLES	FR	IT	UK	CZ	PL	RO
D.CISS_US	0.0316	0.0626	0.107	0.147*	0.0909*	0.270**
	(0.0365)	(0.0605)	(0.0712)	(0.0832)	(0.0472)	(0.109)
D.CISS_EA_excess	0.0118	0.0382	0.0596	0.0904	0.0199	0.200**
	(0.0312)	(0.0484)	(0.0607)	(0.0648)	(0.0418)	(0.0994)
D.SI_DE	-0.000566	-0.000374	-0.00106	0.00148*	0.000242	0.000789
	(0.000496)	(0.000413)	(0.00111)	(0.000760)	(0.000515)	(0.000835)
D.SI_FR	0.000360					
	(0.000318)					
D.SI_IT	0.000889**	0.00141*	0.00163*	0.00198	0.00188***	0.00234*
	(0.000410)	(0.000804)	(0.000875)	(0.00122)	(0.000643)	(0.00122)
D.SI_UK			0.000689			
			(0.000720)			
D.SI_CZ				-0.000194		
				(0.000710)		
D.SI_PL					-6.16e-05	
					(0.000405)	
D.SI_RO						0.000295
						(0.000519)
Observations	58	58	58	58	58	58
R-squared	0.188	0.212	0.146	0.341	0.540	0.378
Prob >F	0.0301	0.1389	0.1038	0.0073	0.0009	0.0009

Notes: The table shows OLS coefficients and the corresponding robust standard errors. The data was aggregated to a weekly frequency. The dependent variable is the DCC between the index returns of the respective country and Germany. CISS denotes the Composite Indicator of Systemic Stress and SI the OxCGRT Stringency Index. The indicators are transformed as described in the text. The underlying period for the subsample is 31 January 2020 - 11 March 2021. Significance levels: *** 1%, ** 5%, * 10%.

intuitively meaningful. For the less developed markets, the coefficient is close to 0.002. An important factor for the relevance of the variable could be the evolution of the index and correlations in calendar week 9 in 2020, which ended on March 1, 2020. The weekly average of the Stringency index more than doubled vis-à-vis the previous week. In the same week, dynamic conditional correlations increased substantially. In many cases, this pattern intensified in the subsequent weeks. Interpreting the results causally, a 30-point increase in the Italian Stringency index would imply a $0.002 * 30 = 0.06$ rise in the DCC.

The results provide additional evidence for the special role of Italy in the transmission of the COVID-19 crisis to the stock markets, which was previously found, e.g., in Just and Echaust (2020). Just and Echaust (2020) note that the situation in Italy was critical for global stock markets because the effects of COVID-19 occurred there earliest and most severely of all European countries. It should be noted that a causal interpretation of the results from these regressions should be taken with caution since there is a considerable risk of omitted variables. Moreover, due to the availability of the individual time series, the number of regressors is very limited. These limitations are discussed in more detail in section 3.5.

3.5 Robustness and Limitations

To investigate if the particular calculation of returns and/or the specific DCC estimation is crucial for our results, we compare our DCCs estimates with an alternative simple measure of correlation. We calculate simple rolling window correlations[6] over a period of the last 100 return observations, i.e., returns between $t-100$ and $t-1$ are considered when estimating the correlation at time t. The stock index returns are calculated as shown in equation 3.1. In order to ensure that the

[6]We used the user-written STATA command "rangestat" written by Robert Picard, Nicholas J. Cox and Roberto Ferrer to calculate rolling window correlations.

results are not significantly influenced by the calculation of the return time series described above, we refrain from making two adjustments in this section. First, null returns are not eliminated. Hence, the underlying data is not adjusted for trading holidays, i.e., by assuming zero returns are the result of exchange holidays. Second, and in contrast to section 3.4, the time series mean is not subtracted from the respective return observation. The samples are divided as in section 3.4, into the GFC period (September 15, 2007 - September 15, 2009), the SDC period (November 1, 2010 - November 1, 2012), the COVID-19 period (March 11, 2019 - March 11, 2021), and the period containing the Russian invasion of Ukraine (June 30, 2021 - June 30, 2022).

Generally, DCCs based on holiday-adjusted return observations and simple rolling window correlations (see figure 3.5) based on the last 100 unadjusted returns show similar patterns. However, different reactions to shocks are not surprising as the change in DCC is driven by the adjustment process described in Engle (2002), while the window size is crucial for simple correlations.

We detect a major difference between DCCs and simple rolling window correlations around the end of October 2008 (see figures 3.3a and 3.5a). The sudden drop in the correlations between the German and other Western European markets was most probably caused by the short squeeze of Volkswagen shares, resulting in a massive surge of the stock price (Allen et al., 2021), and consequently, a high DAX return. This pronounced change in correlations does not show up in the DCC time series as the index of the Czech Republic had a zero return (bank holiday), and the returns were compensating on the next day. The effect in the simple rolling window correlations cancels out after 100 trading days, leading to a sharp increase in correlations between the German market and Italy, France, and the United Kingdom.

Table 3.8 shows summary statistics for simple rolling window correlations based on the last 100 return observations. For the correlations DE-FR, DE-IT, and DE-UK, mean and maxima are close to the DCC summary statistics in table 3.4.

For these three country pairs, the highest absolute difference between maximum DCC and maximum rolling window correlation is less than 0.025 and in most cases, less than 0.01. For CEE markets, DCCs and simple correlations show larger deviations, especially for maximum values. These results provide evidence that different correlation proxies, i.e., the method to estimate time-varying correlations, can lead to more heterogeneous results when the underlying co-movement between the index returns is weaker. The standard deviations of simple rolling window correlations are higher compared to DCCs. Consistent with DCCs, within the crisis periods most rolling window correlations have their maximum during the COVID-19 crisis.

To check if the results depend on the selection of our benchmark market, i.e., Germany, DCCs between the French market and the remaining country indices have been calculated. As explained in section 3.4.1, the time series show very similar patterns and correlations between DCCs where the German market serves as the basis are highly correlated with DCCs based on the French index. This supports the findings on intraday correlations between Western European and CEE markets of Égert and Kočenda (2011).

In the remaining part of this section, we discuss several limitations of our analysis. We use common indices to proxy the stock market of a country, i.e., the DAX for Germany, the CAC40 for France, the FTSE 100 for the United Kingdom, the PX 50 for the Czech Republic, the WIG 20 for Poland, and the BET for Romania. As a caveat, these indices do not necessarily reflect the same underlying industries and have different numbers of constituents. Some studies use industry-specific subindices to account for industry effects of cross-border dynamic correlations in stock markets, e.g., as in Gottschalk (2021). However, following such an approach adds an additional dimension of comparison, which may make the country-specific effect on the overall market more difficult to identify. Considering industry-specific differences can easily lead to a high number of correlations and an ambiguous interpretation.

Institutional features related to the index calculation might lead to different methodologies in determining index values, which could drive return patterns, especially in an intraday setup (Baur and Jung, 2006). As a result, one might misinterpret patterns arising from institutional particularities as country effects. However, there are various studies which use leading stock market indices to calculate returns and subsequently correlations, e.g., Jondeau and Rockinger (2006), Égert and Kočenda (2011), and Okorie and Lin (2021).

Some limitations to our results in section 3.4.2 should also be kept in mind. As shown in table 3.5, the explanatory power measured by R-squared is rather low and does not exceed 0.20 for any regression. For some periods, the F-test implies that we cannot reject the hypothesis that US CISS and EA excess systemic stress are jointly irrelevant for the variation in DCCs. However, the explanatory power improves as we include Stringency indices in the COVID-19 period, as presented in tables 3.6 and 3.7.

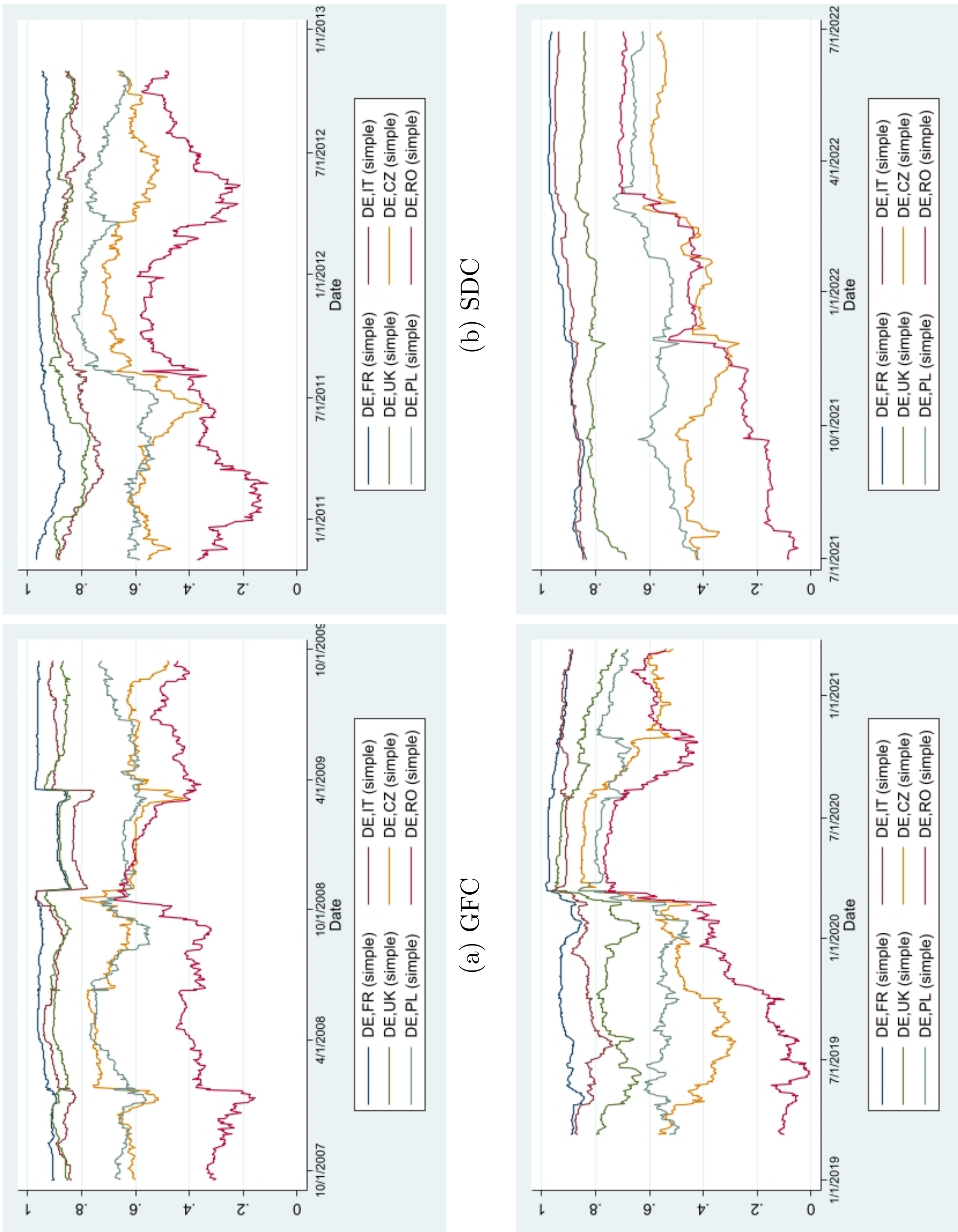
Finally, we have to be aware of potential endogeneity problems. Shocks, measured by the CISS indicators, could hit the considered markets to varying degrees.[7] Hence, country-specific shocks not covered by, but correlated with, systemic stress indicators and/or Stringency indices for the COVID-19 period might have had an effect on DCCs. However, the limited number of observations does not allow for including a large number of regressors.

[7]We would like to thank the participants of the University of Bayreuth Economics Graduate Seminar (summer term 2022) for pointing this out.

Table 3.8: Rolling window correlations - summary statistics

	GFC			SDC			COVID-19			Ukraine		
VARIABLES	Mean	SD	Max	Mean	SD	Max	Mean	SD	Max	Mean	SD	Max
DE,FR (simple)	**0.933**	0.034	0.973	0.932	0.025	0.969	0.923	0.035	**0.983**	0.921	**0.045**	0.974
DE,IT (simple)	0.879	0.042	**0.968**	0.838	**0.055**	0.937	0.873	0.048	0.964	**0.903**	0.036	0.955
DE,UK (simple)	**0.881**	0.022	0.939	0.860	0.041	0.918	0.798	**0.087**	**0.950**	0.821	0.032	0.878
DE,CZ (simple)	**0.639**	0.073	0.806	0.593	0.079	0.722	0.577	**0.172**	**0.856**	0.467	0.085	0.623
DE,PL (simple)	0.656	0.054	0.769	**0.684**	0.090	0.834	0.651	**0.109**	**0.865**	0.585	0.071	0.735
DE,RO (simple)	0.426	0.111	0.682	0.389	0.126	0.593	0.422	**0.250**	**0.771**	**0.427**	0.222	0.717

Notes: The table shows mean, standard deviation (SD) and maximum (Max) of (simple) rolling window correlations within the considered periods. The subsamples are defined as follows: Global Financial Crisis (GFC) 15 September 2007 - 15 September 2009, Sovereign Debt Crisis (SDC) 1 November 2010 - 1 November 2012, COVID-19 11 March 2019 - 11 March 2021, and the period containing the Russian invasion of Ukraine, 30 June 2021 - 30 June 2022.. For a given correlation, the maximum value of mean, SD, and Max for all four periods is reported in bold.



(a) GFC

(b) SDC

(c) COVID-19

(d) Ukraine

Figure 3.5: Rolling window correlations, German stock index

3.6 Conclusions

The aim of this study was to investigate time-varying correlations of the German stock market with Western European (France, Italy, United Kingdom) and CEE (Czech Republic, Poland, Romania) markets in times of elevated systemic stress. We estimated time-varying correlations using the GARCH-DCC approach introduced by Engle (2002). Consistent with the existing literature (e.g., Égert and Kočenda, 2011; Karkowska and Urjasz, 2022) estimates of dynamic correlations are typically higher between Western European markets, compared to CEE markets. Overall, France exhibits the highest correlation with Germany. Interestingly, the mean correlation with the United Kingdom was higher than with Italy in the GFC and the SDC and vice versa in the crisis periods after the Brexit referendum. This might reflect that Brexit marks a turning point in the correlation trend between the UK and continental European markets as discussed in Gottschalk (2021). Within the crises considered, for most countries, the mean correlation is highest in the GFC, while the highest maximum values, as well as standard deviations, are recorded in the COVID-19 crisis. These findings contribute to the literature in demonstrating the unprecedented effects on European stock markets induced by the global pandemic.

In a second step, we regressed weekly means of DCCs on systemic stress in the US and the EA, as measured by the respective CISS indicators. Significant relations are always positive, implying that overall systemic stress increases correlations between countries. Results vary strongly across country pairs and the considered periods. It should be noted that the explanatory power of these models is relatively low. However, when including the OxCGRT Stringency indices in the COVID-19 period, explanatory power increases moderately. We find that DCCs are positively associated with the Stringency index of Italy, which may be the result of Italy's pivotal role in the transmission of COVID-19 fears to global financial markets, as discussed in Just and Echaust (2020).

Our findings based on the selected country indices have important implications for investors and financial stability considerations. On the one hand, we see that some features are stable across the four crises, e.g., the strong French-German co-movement, which exceeds all other correlations. On the other hand, crises such as the global COVID-19 pandemic may induce massive changes in cross-country correlations of equity markets. Higher correlations during times of crisis imply that advantages of international diversification decrease exactly when they are most needed to avoid large losses (Cappiello et al., 2006).

The COVID-19 crisis showed massive stock market reactions, and literature is still growing. An important task for future research will be to shed more light on the actual drivers of short-term correlation patterns between European markets at different stages of development. Focusing on industry-specific co-movements of European stocks, and in particular, between Western and CEE stocks, may help to uncover latent fundamentals of intra-European stock market correlation.

Chapter 4

Conclusions

The central research questions of this thesis deal with the effects of shocks and crises on financial markets and banking stability. The three chapters take different perspectives and investigate financial stability from a prudent regulatory, from a high-frequency market-based, and from a portfolio risk point of view. In all three chapters, there is a special focus on the similarities and differences between European countries, institutions, and markets.

Chapter 1 analyzes the use of the CCyB, a macroprudential policy tool. The instrument was introduced to reduce risks arising from the cyclicality in the financial system. The ESRB framework provides a "guided discretion" approach, which combines rule-based and discretionary components for setting the CCyB. Consistent with the little existing literature, we do not find the credit-to-GDP gap, the recommended rule-based element, to be the crucial driver for national CCyB decisions. However, institutional features, the development of house prices and non-performing loans are relevant variables for explaining CCyB policies in Europe. This raises the question of whether an apparently heterogeneous implementation of macroprudential policies endangers financial stability in Europe.

Due to their business model, banks are particularly exposed to financial cycles as they play an important role in allocating capital to companies and households. As they act as an intermediary, banks are highly relevant for transmitting monetary policy impulses to the real economy. In chapter 2, we investigate the impact of ECB announcements on the market valuation of EU banks. By using bank stock prices as a measure for future expected profitability, we draw market-based conclusions about the relationship between profitability and interest rate movements triggered by central bank communication. Moreover, we analyze the particular role of banks in comparing the reaction of bank stocks to other equities. Following Jarociński and Karadi (2020), we disentangle pure monetary from information shocks by exploiting the relationship of high-frequency movements in market interest rates and stock prices around ECB announcements. We find that the market value of banks is significantly more exposed to information shocks than the market value of other companies after the financial crisis. Strong differences in the reactions of bank stocks during monetary policy announcements provide evidence of a heterogeneous banking landscape not only between EA and non-EA banks, but also between EA banks.

On the one hand, differences between financial systems or countries can hinder the equal transmission of monetary policy or the assessment of the financial cycle. On the other hand, diversity in financial markets and real economies can reduce risks from a portfolio perspective. The first quarter of the 21st century brought several crises, and some of them were accompanied by severe stock market turbulence. In chapter 3, we analyze the correlation between the stock market in Germany and the markets in the Czech Republic, France, Italy, Poland, Romania, and the United Kingdom in times of crisis. In particular, we focus on the co-movement of stock markets during the COVID-19 pandemic and compare the development with the GFC, the SDC and the period containing the beginning of the Russian war in Ukraine. We show evidence for material variation in time-varying correlations by using the GARCH-DCC approach proposed by Engle (2002). The correlations between German and Western-European stock markets are more stable compared to the correlations between Germany and CEE countries. Consistent with recent findings in the literature, we provide evidence that several country-wise correlations soared up to unprecedented levels during the COVID-19 crisis.

Overall, the thesis sheds more light on financial stability considerations in the context of European heterogeneity. It becomes evident that the knowledge of the diversity of European financial markets and the banking sector is required in order to assess the implementation of financial regulation, the transmission of monetary policy, and correlation risks in financial markets. As the process of European integration progresses, it is necessary to continually reassess and illuminate these differences over time.

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