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The Impact of the Level of Interest Rates on the Systemic Risk of Banks

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An Empirical Analysis of Possible Channels

Submitted by
Alexander Nitschke, B.Sc.

Birthday: 22nd November 1995
Address: Jagdfeldring 40
85540 Haar

Student ID: 466233
Email: alexander-nitschke@web.de
Phone: +49 152 046 73 727

Referee:
Prof. Dr. Andreas Pfingsten

Supervisor:
Daniel Platte, M.Sc.

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List of Abbreviations

ΔCoVaR	Delta Conditional Value at Risk by Adrian and Brunnermeier (2016)
adj	Seasonally adjusted
AV13W	13 weeks rolling average
AV26W	26 weeks rolling average
AV52W	52 weeks rolling average
CBOE	Chicago Board Options Exchange
CoVaR	Conditional Value at Risk by Adrian and Brunnermeier (2016)
CRSP	Center for Research in Security Prices
ES	Expected Shortfall
FedFundR	Overnight Effective Federal Funds Rate
FR Y-9C	Consolidated Financial Statements for Holding Companies
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GFC	Global financial crisis
MES	Marginal Expected Shortfall by Acharya et al. (2017)
PERMCO	CRSP permanent code
PERMNO	CRSP permanent number
RD	Reporting day
ROA	Return on assets
ROE	Return on equity
RSSD ID	Replication Server System Database Identifier
RW13W	Rolling window approach with 13 weeks window length
RW26W	Rolling window approach with 26 weeks window length
RW52W	Rolling window approach with 52 weeks window length
SIC	Standard Industrial Classification
SRISK	Systemic risk measure by Brownlees and Engle (2017)
VaR	Value at Risk
VIX	Volatility Index
WRDS	Wharton Research Data Services

List of Symbols

α	Intercept coefficient
β	Slope coefficient
ΔCoVaR	Delta Conditional Value at Risk by Adrian and Brunnermeier (2016)
ε	Error term
ρ	Correlation coefficient
$\phi^{-1}(q\%)$	Quantile function of the normal distribution
a	Coefficient of X in the model regressing M on X in mediation analysis
b	Coefficient of M in the model regressing Y on M and X in mediation analysis
c	Coefficient of X in the model regressing Y on X in mediation analysis (total relation)
C	Specific return realization
c’	Coefficient of X in the model regressing Y on M and X in mediation analysis (direct relation)
CoVaR	Conditional Value at Risk by Adrian and Brunnermeier (2016)
E	Expected value
ES	Expected Shortfall
i	Individual institution
II	Interest income as fraction of total assets
IR	Interest rate
j	Financial system
k	Window length
L	Loss (i.e. negative return) distribution
LEV	Leverage
LIQ	Liquidity as fraction of total assets
LOG(A)	Logarithm of total assets
M	Mediator variable in mediation analysis
Max	Maximum

MES	Marginal Expected Shortfall by Acharya et al. (2017)
Min	Minimum
MTB	Market-to-book ratio
n	Running index of control variables
N	Last out of n control variables
NII	Non-interest income as fraction of total assets
No	Number of observations
NPL	Nonperforming loans as fraction of total assets
P	Probability
PRO	Profitability
q	Confidence level
Q	Quantile
s	Specification of the ΔCoVaR variable
SD	Standard deviation
se	Standard error
t	Time index
u	Specification of the VOL variable
VaR	Value at Risk
VOL	Market volatility
X	Independent variable in mediation analysis
Y	Dependent variable in mediation analysis
Z	Control variable in mediation analysis

1 Introduction

During the latest global financial crisis (GFC), substantial financial disturbances peaking in the bankruptcy of Lehman Brothers in 2008 made apparent how spillover and contagion effects can contribute to financial and economic instability. Since that, studying the characteristics and drivers of systemic risk has experienced special interest in both research and policymaking. Systemic risk can be defined as the risk of an impaired capacity of the financial system as a whole with the potential to detrimentally affect the real economy (Adrian and Brunnermeier, 2016, p.1705). Besides raising attention for the importance of systemic risk, the GFC can furthermore be seen as a starting point of a long era of low interest rates in many industrialized countries. For the scope of the present paper, interest rates refer to the general interest level in an economy that is mainly driven by the central bank's monetary policy. The terms 'interest rate', '(general) interest level' and 'monetary policy rate' are thus used synonymously. A persistently low interest level can substantially impede the net interest margin and profitability of banks (see section 3.2). Besides these two aspects, broad research exists on the relation between the interest level and banks' individual risk taking (see section 3.1). The majority of papers supports the view that low interest rates lead to higher individual risk taking by banks. Against this backdrop, it is all the more surprising that only marginal attention has so far been spent on the relation to banks' systemic risk, despite its potentially higher importance from a financial stability perspective. Therefore, the goal of the present paper is to answer two research questions empirically by using quarterly panel data on the US banking sector between 2005 and 2019. First, it is investigated if and under which sign the interest level and the magnitude of the systemic risk of banks are related. Second, given a significant effect can be detected in the first step, it is analysed through which channels the relation operates.

Thus far, only few contributions deal with the relation between interest rates and systemic risk. Laséen, Pescatori and Turunen (2017) set up a theoretical model where the effect of unexpected monetary policy on systemic risk is ambiguous and dependent on the condition of the financial system. Kurowski and Rogowicz (2017) analyse the relation between monetary policy rates and systemic risk for European countries between 2000 and 2016 empirically. They find evidence in favour of a negative relation. However, they particularly focus on negative interest rates. Furthermore, they use a measure rather unusual for assessing systemic risk in the banking sector and an empirical procedure rather uncommon to arrive at their results. Colletaz et al. (2018) examine how interest rates influence the systemic risk of Eurozone banks between 2000 and 2008. They find no significant influence in the short run but evidence for long-run causality between these measures. Their study is though limited to the time prior to the GFC and the data used are strongly aggregated. Faia and Karau (2018) study the effect of monetary policy on the systemic risk of 29 global systemically important credit institutions between 1992 and 2016. Their evidence supports the increase of systemic risk as an effect of a low interest level. However, using impulse responses, their empirical setting differs from regression approaches mostly used in the literature dealing with banking risk (see section 3). Gang and Qian (2015) apply impulse responses too and find evidence that expansive monetary policy drives up systemic risk in the Chinese banking system after the GFC. The present paper aims to provide two contributions to the existing literature. On the one hand, it is, to the best of the author's knowledge, the first paper that explicitly analyses the relation between the general interest level and systemic risk of banks using panel data and established linear regression models. It thus extends existing literature that analyses the interest rate's influence on individual banking risk. On the other hand, the paper provides a comparative analysis of different channels through which the influence might operate.

This paper proceeds as follows: In section 2, different systemic risk measures are presented and their suitability for the present paper's analysis is discussed. Section 3 develops hypotheses for the empirical analysis by reviewing existing literature on individual risk taking under low interest rates and on potential systemic risk transmission. In section 4, the relation between the interest level and banks' systemic risk is investigated empirically and channels through which the relation might operate are analysed. Section 5 concludes.

2 Review of Literature on Systemic Risk Measurement

2.1 Overview

The definition of systemic risk given in section 1 names an adversely affected capacity of the whole financial system as one of its key characteristics. Measuring this aspect quantitatively is not intuitive, though. Section 2 aims to introduce and discuss selected measures of systemic risk. This is a good starting point for the present paper's discussion for two reasons: First, understanding in depth how systemic risk is quantified by different measures is central to evaluate empirical literature dealing with systemic risk (sections 3.2 to 3.4). Second, discussing the measures with respect to the present paper's research questions and choosing an approach particularly fitting is a linchpin of developing an appropriate empirical setting. Section 2.1 starts by giving an overview of systemic risk measurement. In section 2.2, two promising and commonly used systemic risk measures, namely Delta Conditional Value at Risk (ΔCoVaR) by Adrian and Brunnermeier (2016) and Marginal Expected Shortfall (MES) by Acharya et al. (2017), are theoretically introduced in detail. It is further mentioned how MES can be extended to the systemic risk measure by Brownlees and Engle (2017) (SRISK). After that, the respective strengths and weaknesses of ΔCoVaR and MES are discussed and their suitability for the present paper's research goals is evaluated (section 2.3).

The literature on systemic risk measurement is broad. Multiple approaches exist that aim to capture the systemic importance of banks and their potential to cause negative spillover effects. Broadly speaking, measures regularly found in regulation and academics can be grouped into scoring-based, market-prices-based and other approaches. Scoring-based approaches are commonly used by regulators who aim to identify systemically important institutions and to assign appropriate capital requirements. These approaches assess multiple criteria like size and the extent of cross-border activities separately (e.g. European Banking Authority, 2014 and 2016). Based on a final score over all criteria, a bank's capital requirement is chosen accordingly. In academic research, though, scoring-based measures are rarely applied for several reasons. First, academics aim to use models with a good theoretical foundation while regulators focus on practical implementation aspects (Bisias et al., 2012, p.276). Second, public availability of detailed data transmitted from banks to regulators is usually limited due to confidentiality (Hansen, 2014, p.26). Third, empirical evidence that scoring-based approaches appropriately reflect the true systemic relevance of banks is so far lacking (Hartmann-Wendels et al., 2019, p.342). Fourth, interpreting and comparing these measures across sectors and countries can be seen as challenging.

Market-prices-based approaches aim to partly alleviate these issues and are thus more widespread in research. They employ publicly available market data, e.g. stock prices. The most popular measures are ΔCoVaR, MES and SRISK, an extension of MES. Their characteristic features are discussed in detail in sections 2.2 and 2.3. There is vivid discussion in the literature about the suitability of these and other market-prices-based measures, though. Critical views are for instance given by Rodríguez-Moreno and Peña (2013) and Löffler and Raupach (2018). In contrast, power to forecast financial stress is supported in a study by Döring et al. (2016) for ΔCoVaR, MES and SRISK.

Other measures use different techniques to evaluate a bank's systemic risk. This can for example be done by network approaches (e.g. Gai and Kapadia, 2010; Elliott et al., 2014). Network approaches are analytical tools that model a financial system consisting of nodes (banks) interlinked through edges (cross-sectional contractual relationships) (Bisias et al., 2012, pp.283f).

In the following discussion (sections 2.2 and 2.3), it is focused on two particularly common market-prices-based approaches, namely ΔCoVaR and MES. SRISK is an extension of MES and mentioned, too. A measure for the present paper is chosen among them. This is done for two reasons. First, these measures possess both a sound theoretical foundation and at least some empirical support. Second, they are very common approaches to quantify systemic risk. Relevant literature discussed in sections 3.2 to 3.4 almost exclusively employs market-prices-based approaches and especially the above-mentioned techniques. This ensures good comparability to prior research.

2.2 Delta Conditional Value at Risk and Marginal Expected Shortfall

This section introduces the common market-prices-based systemic risk measures ΔCoVaR, MES and its extension, SRISK. It is shown how ΔCoVaR can be theoretically derived, empirically estimated and extended from a time-invariant to a time-varying specification. Subsequently, the MES approach is explained and its extension to SRISK described.

ΔCoVaR can be derived from the Value at Risk (VaR), a common individual risk measure. If L^{i} is the loss (or negative return) distribution of bank i,[1] the $\mathrm{VaR}_{\mathrm{q}}^{\mathrm{i}}$ can be defined as the loss of i, that is not exceeded with a given confidence level q within a specified time period (Wagner, 2018). The relation can be expressed by equation 1 (Adrian and Brunnermeier, 2016, p.1710).

$$\mathrm{P}\left(\mathrm{L}^{\mathrm{i}} \leq \mathrm{VaR}_{\mathrm{q}}^{\mathrm{i}}\right) = \mathrm{q}\% \tag{1}$$

Since the VaR is an individual risk measure, it captures a bank's risk in isolation and does not necessarily account properly for negative spillover effects (Adrian and Brunnermeier, 2016, p.1706). Thus, Adrian and Brunnermeier (2016, pp.1710f) aim to develop a systemic risk measure where these effects are explicitly accounted for. They extend the VaR as measure for univariate loss distributions to a bivariate setting by introducing another entity j. j can be interpreted as a second individual institution or as the whole financial system. The latter interpretation is used throughout the present paper. $\mathrm{L}^{\mathrm{j}}|\mathrm{C}\left(\mathrm{L}^{\mathrm{i}}\right)$ is defined as the loss distribution of j conditional on a specific return event C of institution i. j's VaR conditional on that specific return event and for the confidence level q, i.e. $\mathrm{CoVaR}_{\mathrm{q}}^{\mathrm{j}|\mathrm{C}(\mathrm{L}^{\mathrm{i}})}$, can be defined by equation 2.

$$\mathrm{P}\left(\mathrm{L}^{\mathrm{j}}|\mathrm{C}\left(\mathrm{L}^{\mathrm{i}}\right) \leq \mathrm{CoVaR}_{\mathrm{q}}^{\mathrm{j}|\mathrm{C}(\mathrm{L}^{\mathrm{i}})}\right) = \mathrm{q}\% \tag{2}$$

The verbal interpretation of equation 2 is as follows: The probability that the percentage loss of j, given some return event of institution i, does not exceed

[1] Using a loss distribution is in line with the usual notation in the VaR literature and done for convenience (Adrian and Brunnermeier, 2016, p.1710). It is computed by multiplying the standard return distribution with -1.

a specified value, $\text{CoVaR}_q^{j|C(L^i)}$, is q percent. Adrian and Brunnermeier (2016, pp.1710f) define two return events $C(L^i)$. One event is defined as the realization of L^i being its median (VaR_{50}^i). The other one is chosen as the VaR of L^i at q (VaR_q^i). In other words, in the first case a regular and uncritical loss event occurs for institution i. In the second case, an extreme loss event is the case. Adrian and Brunnermeier (2016, pp.1710f) define the difference between the two resulting CoVaR-values as the final systemic risk measure, $\Delta\text{CoVaR}_q^{j|i}$. This is shown in equation 3.

$$\Delta\text{CoVaR}_q^{j|i} = \text{CoVaR}_q^{j|L^i=\text{VaR}_q^i} - \text{CoVaR}_q^{j|L^i=\text{VaR}_{50}^i} \tag{3}$$

$\Delta\text{CoVaR}_q^{j|i}$ can thus be verbally interpreted as the increase in the financial system's CoVaR that occurs because bank i experiences a loss amounting to its VaR instead of its median. Figure 1 illustrates this relation graphically.

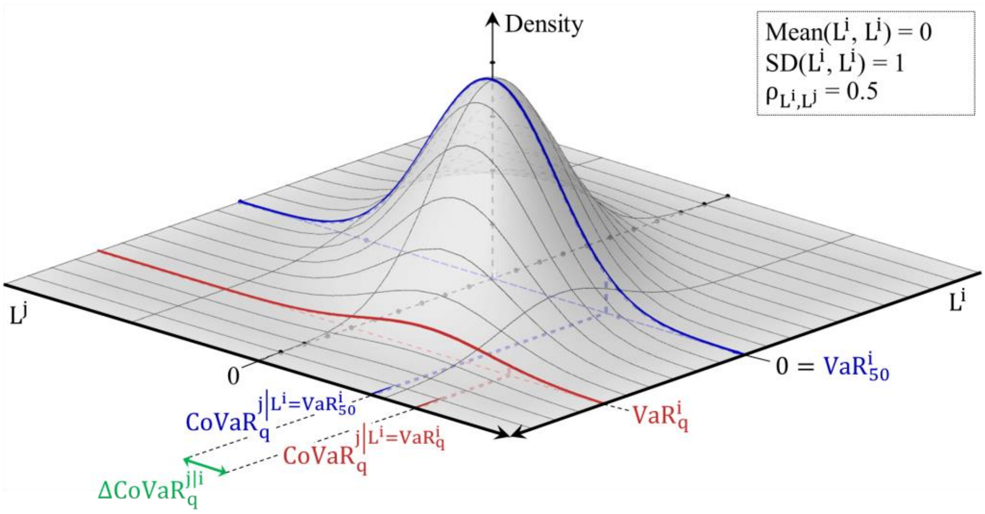

Figure 1: The principle of the Conditional Value at Risk applied to a bivariate normal distribution [Source: Own representation based on Girardi and Ergün (2013, p.3172)]

It is shown a bivariate normal distribution. The left axis depicts the financial system j 's negative return, L^j, and the right axis institution i's negative return, L^i. The mean of both variables is 0, the standard deviation (SD) 1 and their correlation coefficient, ρ_{L^i,L^j}, 0.5. The third axis shows the joint density. In a first step, the two reference values for L^i, VaR_{50}^i and VaR_q^i are computed (see above). Along these return realizations, the bivariate distribution is 'sliced', as represented by the blue and red line, respectively. The slices represent univariate conditional return distributions of the system. The VaR of these conditional distributions, i.e. $\mathrm{CoVaR}_q^{j|L^i=\mathrm{VaR}_{50}^i}$ and $\mathrm{CoVaR}_q^{j|L^i=\mathrm{VaR}_q^i}$ are calculated and $\Delta\mathrm{CoVaR}_q^{j|i}$ computed which is higher than 0 due to $\rho_{L^i,L^j} > 0.5$.

Having introduced the concept of ΔCoVaR theoretically, the question remains how to calculate ΔCoVaR using empirical data which do not follow a prespecified distributional form. Adrian and Brunnermeier (2016, pp.1716f) propose using quantile regressions. Whereas in least square regressions, the realization of the independent variable is used to estimate the expected value of the dependent variable, quantile regressions estimate its quantile (e.g. Koenker, 2005; Furno and Vistocco, 2018). The application of quantile regressions to i’s and j’s loss distributions is shown in equation 4 (Adrian and Brunnermeier, 2016, p.1716).

$$\hat{L}_q^{j|L^i} = \hat{\alpha}_q^i + \hat{\beta}_q^i L^i \tag{4}$$

$\hat{L}_q^{j|L^i}$ is the predicted value of the q percent quantile of the system’s return, conditional on institution i’s return realization L^i. $\hat{\alpha}_q^i$ and $\hat{\beta}_q^i$ are regression coefficients. When inserting VaR_q^i into equation 4, the predicted value equals $\mathrm{CoVaR}_q^{j|L^i=\mathrm{VaR}_q^i}$ as shown in equation 5 (Adrian and Brunnermeier, 2016, p.1717).

$$\mathrm{CoVaR}_q^{j|L^i=\mathrm{VaR}_q^i} = \hat{\alpha}_q^i + \hat{\beta}_q^i \mathrm{VaR}_q^i \tag{5}$$

$\mathrm{CoVaR}_q^{j|L^i=\mathrm{VaR}_{50}^i}$ is calculated analogously by inserting VaR_{50}^i. Both values are inserted in equation 3 as before to compute $\Delta\mathrm{CoVaR}_q^{j|i}$.

So far ΔCoVaR is time-invariant. This means that there is only one constant systemic risk estimation per institution i over the whole sampling period. Thus, in order to capture the time variation of systemic risk, a time index has to be added to equation 3. This results in the formula displayed in equation 6 (Adrian and Brunnermeier, 2016, p.1718).

$$\Delta CoVaR_{q,t}^{j|i} = CoVaR_{q,t}^{j|L^i=VaR_q^i} - CoVaR_{q,t}^{j|L^i=VaR_{50}^i} \tag{6}$$

However, while a time-dimension can be simply added theoretically by including a time index as shown above, actually estimating time-varying ΔCoVaR-values from empirical data is less trivial. The estimation method used for time-invariant ΔCoVaR cannot be applied one to one to time-varying ΔCoVaR. There are three potential ways to estimate time-varying ΔCoVaR-values. They are quickly presented in the following. Their respective applicability for the present paper's research goals is discussed in section 2.3.

The first technique is proposed by Adrian and Brunnermeier (2016, pp.1718f). In their empirical analysis, VaR and ΔCoVaR is estimated as function of lagged economic state variables. The authors choose liquid and tractable variables that they consider to be particularly suited in reflecting the time variability in the conditional moments of security returns, including different variables related to interest rates. The criticality of this feature with respect of the present paper's research environment is discussed in section 2.3. The second approach is proposed by Girardi and Ergün (2013) who estimate time-varying ΔCoVaR-values by a multivariate Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model. GARCH is a technique introduced by Bollerslev (1986) to model and forecast the volatility of time series of financial data. It assumes that the variance of a time series at time t can be predicted by its past variances and error terms. A standard GARCH model that predicts the variance of a time series by its one period lagged error term and its one period lagged variance is called GARCH(1,1) model. Adrian and Brunnermeier (2016, pp.1733f) show that assuming i's and j's loss distributions to be normal, $\Delta CoVaR_{q,t}^{j|i}$ can be computed as shown in equation 7.

$$\Delta CoVaR_{q,t}^{j|i} = \Phi^{-1}(q\%)\rho_t^i SD_t^{system} \tag{7}$$

ρ_t^i is the correlation coefficient, that is obtained as a direct output of the GARCH calculation. SD_t^{system} is the standard deviation of the system return and $\Phi^{-1}(q\%)$ the quantile function of the normal distribution. In the third approach, rolling window regressions, quantile regressions are used as described above but only for a part of the sample. More precisely, a subsample of stock and system returns is taken at each point in time t that reaches back k periods. k is called window length. In the literature, ΔCoVaR is estimated using a rolling window approach for instance in a study by Chu et al. (2020).

Another popular market-prices-based approach is the MES by Acharya et al. (2017). It builds on the individual risk measure Expected Shortfall (ES). The ES_q^i is the expected value of i's loss distribution L^i, given that the loss is equal or higher than VaR_q^i (Acharya et al., 2017, p.6). Formally, the relation can be described as in equation 8.

$$ES_q^i = E(L^i | L^i \geq VaR_q^i) \tag{8}$$

Acharya et al. (2017, p.15) extend the ES concept such that it captures systemic instead of individual risk. They show that the MES_q^i can be estimated from empirical data as the average return of institution i in the q percent days with the worst returns in the system, as shown formally in equation 9.

$$MES_q^i = \frac{1}{\#\text{days}} \sum_{t:\ \text{system is in its } q\% \text{ tail}} L_t^i \tag{9}$$

The MES thus measures the distress of an individual institution conditional on a stress event in the financial system whereas ΔCoVaR does the opposite: It measures the financial system's stress conditional on an individual institution being in financial distress (Acharya et al., 2017, pp.5f). However, even though being unusual in research, both measures could in principle be adjusted to measure the other direction, respectively (e.g. the so-called Exposure-ΔCoVaR by Adrian and Brunnermeier (2016, p.1714)).

Brownlees and Engle (2017) extend MES to SRISK by additionally including accounting data, e.g. leverage. SRISK can be interpreted as the minimum capital an institution needs in a financial crisis to prevent bankruptcy.

However, for the present paper’s goals it is more convenient to include leverage as explanatory variable in regressions and not to use it as an estimator for the systemic risk measure (see sections 3.1 and 4.1.2). Thus, section 2.3 chooses the best fitting approach between ΔCoVaR and MES.

2.3 Discussion

Having an overview of the measurement techniques of systemic risk gives the opportunity to decide which approach best reflects the present paper’s research goals. Literature contributions employing this measure (sections 3.2 to 3.4) are of particular interest and it is used in the present paper’s empirical analysis (section 4). Given their profound theoretical foundation and broad dissemination in existing literature, ΔCoVaR and MES are at first glance both suitable candidates. A starting point for a deeper discussion is comparing the respective individual risk measures both approaches build on. Two aspects speak in favour of the ES and thus of the MES. In contrast to the VaR, the ES captures all losses beyond the q percent VaR threshold and thus better reflects very asymmetric payoff profiles. Furthermore, the ES is a coherent risk measure in the sense that it does, unlike the VaR, not fail to fulfill the subadditivity axiom (Artzner et al., 1999). Subadditivity means that the risk of a portfolio is never bigger that the sum of the portfolio components. Though, Yamai and Yoshiba (2002) find that for the same level of accuracy, the ES requires a larger sample size than the VaR when measured with historical data. This is due to the fact that extreme events are very rare. For short sapling periods, the MES can thus have large estimation errors. This aspect is particularly relevant for the present paper’s research goal. In order to capture the time variation in systemic risk, e.g. by rolling window regressions, sampling periods have to be kept rather short.

Moreover, not only the required sample size speaks in favour of choosing ΔCoVaR. From a societal perspective, it seems to be more relevant to capture the negative spillover effect that an institution exerts on the financial system than the other way around. This direction is in the original definition only measured by ΔCoVaR. Even though MES could in principle be conditioned in the same direction as ΔCoVaR, this would mean largely forsaking comparability to prior research because MES is usually used in its original specification. As a result, ΔCoVaR is more suited when taking a macroeconomic perspective whereas MES does rather capture a risk management view. Last but not least, according to the present paper's author's view, ΔCoVaR distinguishes more precisely between systemic and individual risk components. This can be said due to the feature of ΔCoVaR that is shown in equation 6: ΔCoVaR is the difference in the conditional VaR between a stress state and a normal state. In this way, ΔCoVaR captures in the inner sense the 'extra portion' of risk that is due to contagion. This clear distinction is not in the same way given in the MES. All in all, ΔCoVaR can be seen as the measure more fitting to the present paper's research questions. It is thus chosen as the systemic risk measure in the empirical analysis.

Having chosen ΔCoVaR as risk measure, the question remains which estimation technique (see section 2.2) fits best. The estimation technique using lagged state variables cannot be evaluated as a suitable measure. As mentioned earlier, different variables that Adrian and Brunnermeier (2016, p.1718f) propose directly or indirectly depend on the interest level. Using interest rates to estimate ΔCoVaR before conducting the actual empirical analysis means that interest rates are used two times as explanatory variable. However, both GARCH and the rolling window approach do not possess this feature and are thus in principle suited. GARCH has the advantage that it provides an estimate of ΔCoVaR precisely at t and is not biased by older volatility realizations. Furthermore, its values can be estimated from the second observation of the sample until the end. Rolling window regressions are available only from time 0+k onwards and take into account all observations from t-k to t equally. However, the rolling window approach has the advantage that actual return data is used. Because both approaches have different strengths, both are suited with respect to the present paper's research goals and thus employed in the empirical analysis in section 4.

3 Review of Literature on the Relation between Interest Rates and Systemic Risk

3.1 Overall Relation and the Search for Yield Channel – Insights from Banks' Individual Risk Taking

3.1.1 Theoretical Background

As mentioned in section 1, literature that relates the level of interest to systemic risk of banks is rather scarce. However, the interest level's influence on the individual risk of banks has received broad attention from both a theoretical and empirical point of view. Clearly, individual and systemic banking risk are different concepts (see section 2.2). Still, when relating both to the interest level, similar underlying risk channels can be assumed for both (e.g. Colletaz et al., 2018; Faia and Karau, 2018). Thus, the goal is to transfer applicable concepts and insights to the analysis of systemic risk. Section 3.1.1 compares theoretical concepts relating interest rates with banks' individual risk taking that receive particularly high attention in the literature. Section 3.1.2 discusses to which extent they can be supported empirically.

A first indication how interest rates and risk taking are connected is given by classical portfolio theory. Fishburn and Burr Porter (1976) show that lower interest rates, i.e. a lower return on safe assets, decrease their attractiveness relative to risky assets. This induces agents to reallocate their portfolios towards the latter. The relation is shown to hold under relatively general conditions including risk neutrality and most forms of risk aversion. Though being intuitive, this setting is strongly simplified and does not capture the complex business environment of banks sufficiently.

Another stream of literature, which Dell'Ariccia et al. (2017, p.614) summarize as risk-shifting models predicts an opposite effect. One example of such a model is the credit-rationing model of Stiglitz and Weiss (1981). In this model, borrowers conduct business models characterized by return distributions with the same expected value but different standard deviations. For the lenders, the standard deviations of the projects are unobservable. It is shown that increasing the loan rates can lead to a higher number of loan applicants with high risk, i.e. adverse selection, when borrowers cannot choose their projects' riskiness. If they can do so, existing borrowers of the bank have incentives to increase their business risk leading to moral hazard. In summary, higher lending rates can make the loan portfolio of the lender more risky (Stiglitz and Weiss, 1981).

Dell'Ariccia et al. (2017, p.614) find, on the one hand, risk shifting models to have in common that they predict a positive relation between interest rates and individual banking risk. On the other hand, they state that risk shifting models assume in some form information asymmetry and limited liability. Dell'Ariccia et al. (2017, p.614) argue that thus, in these models the effect of interest rate on risk is expected to be stronger for banks with high leverage where both imperfections are more pronounced. It is important to note that leverage might therefore be a suited proxy to empirically test for risk shifting models. In the following it is explained, what overall effect alternative theoretical settings imply and how they are related to banks' leverage. Like risk-shifting models, all of these reflect typical characteristics of the banking business more extensively than classical portfolio theory does.

Dell'Ariccia et al. (2014) set up a model that aims to combine classical portfolio theory with risk-shifting models. It is based on two common assumptions. First, banks have limited liability and choose the costly effort with which they monitor creditors. Second, a bank's cost of debt as well as the interest paid on loans outstanding both depend on the risk-free interest rate. There are furthermore two scenarios that have to be distinguished when analysing the effect of a change in the interest rate on a bank's risk. If a bank can adjust its capital structure, a reduction of the interest rate will induce it to increase leverage and reduce monitoring. This means a rise of the bank's risk. If a bank cannot adjust its capital structure, the effect is ambiguous and depends on the respective bank's capital structure. Lowly levered banks respond to a reduced risk-free rate by decreasing monitoring effort leading to higher risk. Banks with high leverage, however, may increase monitoring and decrease risk (Dell'Ariccia et al., 2014).

The second specification seems to be closer to reality. At least, larger adjustments of the capital structure in the short run can be seen as rather difficult to be conducted by a bank. As explained by Dell'Ariccia et al. (2014, p.74), institutions in reality face high financing costs, especially during economic downturns, and a binding minimum capital requirement by regulators. Under this assumption, ex-ante leverage is again a central measure to empirically assess whether the model's predictions hold.

An alternative explanation how interest rates are supposed to influence the risk taking of financial institutions is called search for yield and introduced by Rajan (2006, pp.501, 517f). He describes different reasons why low interest rates can incentivize financial institutions to increase risk. For instance, life insurance companies and pension funds conduct maturity transformation in their balance sheets: Long-run liabilities are opposed to short-term assets. When interest rates on short-term assets are decreased more than those of long-run liabilities, the financial institution might have to increase risk in order to avoid bankruptcy. Furthermore, compensation contracts of investment managers regularly include return targets that can only be achieved by higher portfolio risk when risk-free rates are low (Rajan, 2006, pp.501, 517f).

The concept of search for yield can, with some caution, be transferred to banks as well. It is, however, important to remember that maturity transformation of banks works in the opposite direction compared to life insurers and pension funds: Long-term investments of entrepreneurs are financed via loans with short-term capital obtained from savers. This somehow contradicts the first potential reason for search for yield mentioned above (Dell'Ariccia et al., 2017, p.615). However, this does in no way mean that banks cannot be subject to search for yield in a low interest environment. The profit opportunities of a bank are, among other factors, determined by the net interest margin, i.e. the difference between the interest rates paid to the bank for loans and those paid to savers by the bank. Empirical evidence discussed in section 3.2 shows that both net interest margin and profitability suffer under low interest rates. Furthermore, compensation contracts might support excessive risk taking as described above. In consequence, banks might have an incentive to search for yield by choosing particularly risky assets when the interest level is low (e.g. Dell'Ariccia et al., 2017, p.615; Jiménez et al., 2014, pp.464f). This corresponds to very similar problems in banking and corporate finance. Under financial distress, shareholders and managers might have incentives to take exessive risky strategies from whose success they profit wheras debtholders or depositors bear the risk of failure. Such a behaviour is known as 'gambling for resurrection' (Hartmann-Wendels et al., 2019, pp.328f) in banking or 'asset substitution problem' in general corporate finance (Jensen and Meckling, 1976; Berk and DeMarzo, 2020, pp.603f). It can be shown that these agency problems are more present in highly levered firms (e.g. Hartmann-Wendels et al., 2019, p.329). The same rationale holds for search for yield: The negative relation between interest rates and risk is expected to be stronger for banks with low capitalization (Dell'Ariccia et al., 2017, p.615). The opposite is expected under the model of Dell'Ariccia et al. (2014) which shows that leverage is a suitable proxy to empirically assess both models' predictions.

In summary, the theoretical models presented in this section provide very heterogenous predictions under which sign interest rates and banks' risk taking are related. This underlines the need to address the influence of the interest level on banks' risk empirically. Furthermore, because playing a key role in three of the four theoretical concepts described above, analysing the interaction of the effect with leverage is of particular relevance. Empirical contributions investigating the models' predictions are discussed in section 3.1.2.

3.1.2 Empirical Evidence

Empirical literature on the relation between the interest level and banks' individual risk is less heterogenous than the theoretical models presented in section 3.1.1, at least with respect to the sign of the relation. Studies analysing the overall connection are numerous. Two contributions relate interest and individual risk of banks by employing accounting data. The first study by Delis and Kouretas (2011) employs data from Euro area commercial, savings and cooperative banks between 2001 and 2008. They analyse the effect of low interest rates, on the one hand, on the ratio of risky assets. Risky assets are all assets excluding cash, government debt and balances due from other institutes. On the other hand, they analyse the effect on the ratio of nonperforming loans to total loans. Both effects are found to be negative and significant (Delis and Kouretas, 2011).

In a slightly modified setting with a different geographical focus, Delis et al. (2011), analyse risk implications of monetary policy on US commercial banks. This is done by using quarterly data between 1985 and 2010. As risk measures, risky assets (see definition above) and the Z-index are analysed. The Z-index is the sum of the return on assets (ROA) and the equity-to-assets ratio, both divided by the standard deviation of ROA. It is interpreted as a probability of default. Results with respect to both measures support higher risk under low interest rates (Delis et al., 2011).

Alternatively to analyse individual risk via accounting data, Maddaloni and Peydró (2011) analyse banks' lending standards for the US and Euro area. They use quarterly data on bank lending surveys between 1991 and 2008 for the US and between 2002 and 2008 for the Euro area. It is found that low short-term interest rates are related to a significant softening of credit lending standards for business and private loans, especially in times of prolonged low interest. For long-term rates, mixed evidence is found. However, it is not analysed how the effect interacts with leverage (Maddaloni and Peydró, 2011).

All three research contributions mentioned support the view that interest rates and individual risk are negatively related. This speaks against pure risk-shifting models that predict a positive connection. To gain a deeper understanding of the channels behind that relation, three more recent contributions which focus more on its interaction with leverage are discussed hereafter.

In the first relevant study, Dell'Ariccia et al. (2017) employ data on US banks' corporate loans including their credit ratings between 1997 and 2011. It is focused on loans granted to companies for the first time. The aim hereby is to reduce endogeneity issues, i.e. the possibility that monetary policy might be influenced by banks' loan portfolios. It is found evidence that lower interest rates are associated with the granting of riskier loans by banks. The relation is found to be stronger for banks with low leverage. This is in line with a risk-shifting effect (Dell'Ariccia et al., 2017) and thus with the combined model of Dell'Ariccia et al. (2014) presented in section 3.1.1.

The second contribution by Jiménez et al. (2014) has a closely related research objective but provides an important difference regarding its results. Jiménez et al. (2014) analyse banks' monetary policy induced change in risk by focusing on loan quality. For this, data from the Spanish credit register is assessed between 2002 and 2008. The authors first state that a change in the interest level can affect quality and volume of both demand and supply of loans. Therefore, they choose a research design that aims to disentangle the effect on the quality of credit supply from the other effects. They use a two-stage regression model. In the first stage, it is assessed how many loans are granted to applicants depending on their credit quality. In the second stage, the amount of money that is granted given a loan application has been successful in the first stage is measured. Moreover, the probability that the loans granted default in the future is evaluated. The authors provide evidence that banks grant more loans to firms with high credit risk when overnight interest rates are low. More money is lent to these firms and less collateral required. The probability of future loan defaults if furthermore higher for these firms. This is overall supportive of a risk-increasing effect of low interest rates. However, contrary to Dell'Ariccia et al. (2017), the effect is especially pronounced for less capitalized banks. This can be interpreted as evidence for search for yield. No effects are found for long-term interest rates (Jiménez et al., 2014).

A third study by Ioannidou et al. (2015) supports the evidence in favour of search for yield. Ioannidou et al. (2015) analyse the connection between monetary policy rates and the riskiness of bank loans in the Bolivian market. Even though the Bolivian banking market can hardly be compared to industrialized markets, it is assessed to provide an almost experimental setting for the transmission of interest rates to risk. During the sampling time, the Bolivian banking sector has largely used US dollars as de facto currency. The exchange rate to the home currency has been almost fixed (crawling peg) and capital restrictions have been low. However, the US and the Bolivian economy are only weakly synchronized. This means that US monetary policy is an exogenous factor from the Bolivian economy's point of view. The effect of an exogenous change is analysed by using monthly data on the Bolivian credit register from 1999 to 2003. It is found that lower monetary policy rates are linked with the granting of ex-ante riskier loans with ex-post worse performance. An interesting side result is that banks with higher leverage increase their risk more when interest rates are low (Ioannidou et al., 2015, p.129).

In summary, empirical evidence broadly supports a negative and significant effect of monetary policy rates on banks' risk taking. This means that pure risk-shifting models cannot be supported using empirical data. However, there are both results in line with a risk shifting as well as the search for yield explanation. In the following, alternative channels from systemic risk literature are discussed. In accordance with the literature reviewed in section 3.1.2, it is focused on channels that correspond to a negative overall relation.

3.2 Profitability as Potential Channel

One potential channel through which interest rates and systemic risk might be negatively connected is profitability. This requires that first interest rates and profitability and second profitability and systemic risk are related in a proper way. This section puts together the two corresponding streams of literature and assesses if they support a systemic risk transmission via profitability.

The relation analysed in the first stream of literature captures a phenomenon that is frequently named as one of the three major challenges in modern banking practice, next to regulatory requirements and digitalization: Lower profit opportunities under a low interest rate environment. Academic evidence supports this perception. Alessandri and Nelson (2015) show that in a monopolistically competitive banking market model, lower short term interest rates compress the net interest margin. Empirically, the relation between interest rates and net interest margin as well as profitability is found to be negative in the short run but positive in the long run for UK banks between 1992 and 2009. Claessens et al. (2017) analyse a large sample of banks from 47 nations between 2005 and 2013. They find that low interest rates are connected with lower net interest margins and lower profitability of banks. The link is found to be the more pronounced the longer the interest level is low. Evidence by Neuenkirch and Nöckel (2018) supports the positive relation between interest rates and net interest margins for European banks between 2003 and 2016. Molyneux et al. (2019) find that negative interest rates are connected with low net interest margins and profitability. A contrary view is given by Altavilla et al. (2018). They argue that when controlling for endogeneity of monetary policy to current and expected future financial and economic conditions, interest rates are not significantly related to banking profits. This view is rather an exception in existing literature, though.

The link between profitability and systemic risk constitutes the second stream of literature. Theoretical literature on the relation is scarce and empirical results are heterogenous. Anginer et al. (2014, p.14) find no significant relation between ROA and systemic risk. This is confirmed by Döring et al. (2016, p.39) for the link between ROA and MES, ΔCoVaR and SRISK. In the paper of Chu et al. (2020, pp.4819, 4825), sign and significance of the relation is highly dependent on the model specification and measure of systemic risk. A positive and significant connection between ROE and systemic risk is found by De Jonghe (2010, p.406). ROE is though partly driven by leverage and thus the result might capture a positive relation between leverage and systemic risk. In contrast, Engle et al. (2014, pp.51-54) find a negative and significant relationship between ROA and MES.

In summary, literature broadly supports the view that low interest rates are connected with low profitability. The link between low profitability and systemic risk is much less clear, though. However, because there is evidence for a (negative) relation in some contributions, analysing profitability as a channel is promising and thus conducted in section 4.

3.3 Non-Interest Income as Potential Channel

This section discusses whether non-interest income can be considered as a transmission channel of a negative interest rate-systemic risk relation. As in the case of profitability, this section reviews existing literature with respect to the two relations necessary: First, a relation between interest rates and non-interest income and, second, between non-interest income and systemic risk.

Regarding the first relation, the intuition is described e.g. by Claessens et al. (2017, p.5) and Saunders et al. (2020, p.5): In a low interest rate environment with shrinking net interest margins (see section 3.2), the relative attractiveness of generating non-interest income instead of the interest income rises. One could thus expect a corresponding shift in the income generation of banks. Evidence whether non-interest income is actually profitability-enhancing is mixed, though. In a recent contribution, Saunders et al. (2020) review existing contradictory literature on the relation and reassess it using quarterly data on US banks between 1984 and 2013. They employ different methodologies and subsample periods and come to the conclusion that findings are highly dependent on these two factors. However, they provide evidence speaking in favour of a profitability-enhancing effect of non-interest income for the recent past. Literature is moreover contradictory if banks rely more on non-interest income under low interest rates. On the one side, a negative relation between interest rates and non-interest income is empirically found by Borio et al. (2017, pp.56f) for international banks between 1995 and 2012. On the other side, Altavilla et al. (2018, p.549) find no significant relation when employing quarterly data on euro area banks between 2000 and 2016.

As a next step, the second relation is discussed. To understand why non-interest income could be a driver of systemic risk, it is worth to consider two empirical findings. On the one hand, non-interest income is more volatile than interest income (DeYoung and Roland, 2001; Brunnermeier et al., 2020, pp.233f). On the other hand, it is procyclical and positively correlated with the mergers and acquisitions activity (Brunnermeier et al., 2020). Acharya (2009) shows theoretically that such correlated activities can under limited liability increase systemic risk. Similar implications are given by a theoretical model by Allen et al. (2012). Empirical evidence of the relation is mixed, though.

Brunnermeier et al. (2020) assess data on US publicly traded financial institutions between 1986 and 2017. It is estimated how the share of non-interest income to total assets of a bank drives ΔCoVaR and MES when controlling for various accounting variables. These accounting variables are selected based on prior literature on cross-sectional systemic risk determinants. They find that the non-interest income share is positively and significantly connected to ΔCoVaR and MES (Brunnermeier et al., 2020).

This is in line with evidence by De Jonghe (2010). He investigates the relation between non-interest income and systemic risk for European banks between 1992 and 2007. He finds a positive and significant connection. However, he measures systemic risk by a firm's tail beta which is more related to systematic risk and uncommon in systemic risk literature. De Jonghe et al. (2015) analyse the link between non-interest income and MES separately for small and large banks by employing data on institutes all over the world between 1997 and 2011. Their analysis provides evidence that the link is positive and significant for small banks but negative and significant for large banks.

The findings supporting a significant, mostly positive, relation are not in line with evidence from Saunders et al. (2020, p.59). They analyse the link between non-interest income and systemic risk for US banks using quarterly data reaching from 1987 to 2013. Evidence for a positive relation is rather weak. The connection to MES is insignificant for the whole sample and different subsamples. For ΔCoVaR, the sign of the relation and its significance are highly dependent on the model specification. All in all, their evidence does not provide convincing support for a correlation between interest and systemic risk (Saunders et al., 2020, p.59).

There are further contributions analysing the connection between non-interest income and systemic risk for US banks who find no significant relation. When analysing a large dataset of banks from various countries, Weiß et al. (2014) find little to no empirical evidence that non-interest income drives systemic risk. However, it is surprising that they find overall low evidence for the role of cross-sectional factors like leverage and size in determining systemic risk. Engle et al. (2014) provide differentiated results when analysing data on large banks from various countries between 1996 and 2010. They find a positive and significant relation between non-interest income and MES only for banks in countries with low market concentration (e.g. Germany and US). For countries with high concentration (e.g. Canada and Australia), a negative relation is found. In both cases it depends on the respective model specification whether or not the respective relation is significant.

All in all, literature provides mixed evidence of both a (negative) interaction between interest rates and non-interest income as well as a (positive) relation between non-interest income and systemic risk. Still, some papers support the view that non-interest income could transmit a negative relation between interest rates and systemic risk. It is thus analysed empirically in section 4.

3.4 Income Stream Diversification of the Financial System as Potential Channel

The last potential channel through which a negative interest rate-systemic risk relation might materialize is the diversification of the whole financial system with respect to the two major income streams, i.e. non-interest and interest income. This requires two relations: First, between interest rates and income stream diversification and, second, between income stream diversification and systemic risk. Both are investigated in this section by reviewing literature.

The rationale of the first relation is initially connected to the discussion on the role of the non-interest income share in section 3.3. Claessens et al. (2017, p.5) explain that under low net interest margins, non-interest income becomes more attractive relative to interest income. However, adjusting the structure of income streams might be quite challenging for banks. Claessens et al. (2017, p.5) state that cross-sectional differences between banks, e.g. their size or their business model, can be expected to influence to which extent institutes can switch to non-interest income. This means that some banks can relatively easily switch to non-interest income whereas others cannot change the relative weight of the two income streams substantially. Given that the ability to switch to non-interest income is not driven by the prior share of non-interest income of a bank, this could lead to a situation where the share of non-interest compared to interest income is more scattered between the different banks under low interest rates. For the financial system, this would mean a higher income stream diversification. Descriptive statistics of Saunders et al. (2020, p.45) slightly support that the ratio of non-interest to interest income is more scattered in times of prolonged low interest rates. Heterogeneous firm responses to structural changes are furthermore documented for other areas, e.g. technological changes (Eggers and Park, 2018). Unfortunately, more reliable evidence on the described mechanism is lacking. This, however, even more motivates a corresponding analysis in section 4.

To be considered as channel in the sense of the present paper's analysis, income stream diversification of the financial system has to be expected to drive systemic risk. Chu et al. (2020, p.4812) comes to the conclusion that literature relating diversification to systemic risk is scarce. There are few contributions, though. Caccioli et al. (2014) develop a network model of contagion and show that diversification can increase systemic risk, even when being advantageous from an individual bank's perspective. Here, the main intuition is that diversification leading to more similar banking portfolios creates a situation where a higher number of banks suffers under adverse shocks due to common asset holdings and interconnectedness. Both higher diversification and higher asset similarity are not unlikely to be given at the same time in the present research setting. If banks that are increasing non-interest income do so by primarily expanding activities that have so far been the domain of competitors, the situation could be given. Similar mechanisms as in Caccioli et al.'s (2014) paper are found by Wagner (2010) and Ibragimov et al. (2011) in their theoretical models. Greenwood et al. (2015) find ambiguous effects of diversification on systemic risk in their theoretical setup, depending on asset liquidity. In an empirical contribution on geographic diversification, Chu et al. (2020) find more diversification to be related to higher asset similarity and systemic risk.

In summary, literature supporting a negative relation between interest rates and income stream diversification is scarce. A positive relation between income stream diversification and systemic risk is supported, though. Investigating the channel is expected to generate interesting insights and is thus conducted in section 4.

3.5 Development of Hypotheses

This section develops hypotheses for the empirical analysis in section 4 based on the literature review conducted in sections 3.1 to 3.4. Existing literature broadly supports the view that a low interest rate environment is related to higher individual risk of banks. This finding is expected to be transferable to the interest rate-systemic risk relation resulting in the following hypothesis:

> H1: In the banking sector, low interest rates are related to high systemic risk.

Evidence given in section 4.3 supports H1. It is thus conducted a deeper analysis with the goal to find through which channels the relation operates. The first potential channel that is analysed is search for yield. Search for yield is an agency problem that is expected to be stronger in banks with high leverage (see section 3.1). Leverage is thus a suited proxy for search for yield behaviour. An opposite role of leverage would be consistent with an asset-substitution effect. Because existing evidence is slightly more in line with search for yield, the following hypothesis is set up:

> H2: In the banking sector, low interest rates are related to high systemic risk due to search for yield.

Besides the hypotheses based on the individual risk-taking literature, this paper tests for three more channels by putting together different streams of the literature on systemic risk. The first of them is profitability (see section 3.2). The following hypotheses are proposed:

> H3a: In the banking sector, low interest rates are related to low profitability.

> H3b: In the banking sector, low profitability is related to high systemic risk.

> H3c: In the banking sector, low interest rates are related to high systemic risk through low profitability.

As discussed in section 3.3, non-interest income constitutes another potential channel. This leads to the following three hypotheses:

> H4a: In the banking sector, low interest rates are related to a high share of non-interest income to total assets.

> H4b: In the banking sector, a high share of non-interest income to total assets is related to high systemic risk.

> H4c: In the banking sector, low interest rates are related to high systemic risk through a high share of non-interest income to total assets.

The last channel to be analysed builds on income stream diversification of the financial system (see section 3.4). The following hypotheses are set up:

> H5a: In the banking sector, low interest rates are related to a high diversification of income streams in the system.

> H5b: In the banking sector, a high diversification of income streams in the system is related to high systemic risk.

> H5c: In the banking sector, low interest rates are related to high systemic risk through a high diversification of income streams in the system.

Having stated the research hypotheses, section 4 tests them empirically.

4 Empirical Analysis

4.1 Methodology

4.1.1 Overall Relation

This section aims to define an appropriate empirical methodology in order to analyse if and under which sign the interest level is related to banks' systemic risk. This can be achieved by linearly regressing ΔCoVaR on the interest rate (IR). Variables that capture the different channels described in section 3 are already included in the main model to ensure a continuous analysis. Furthermore, various other potential drivers of systemic risk are included as control variables. The regression model is given by equation 10.

$$\Delta \mathrm{CoVaR}^{j|i}_{0.99,t,s} = \alpha^{i} + \beta_1 \times \mathrm{IR}_{t-k} + \beta_2 \times \mathrm{PRO}^{i}_{t-k} + \beta_3 \times \mathrm{NII}^{i}_{t-k} + \beta_4 \times \mathrm{II}^{i}_{t-k} + \beta_5 \times \mathrm{SD(NII/II)}_{t-k} + \beta_6 \times \mathrm{LOG(A)}^{i}_{t-k} + \beta_7 \times \mathrm{LEV}^{i}_{t-k} + \beta_8 \times \mathrm{MTB}^{i}_{t-k} + \beta_9 \times \mathrm{LIQ}^{i}_{t-k} + \beta_{10} \times \mathrm{NPL}^{i}_{t-k} + \beta_{11} \times \mathrm{VOL}_{t,u} + \varepsilon^{i}_{t} \quad (10)$$

In the following description, the subscripts of the variables are dropped for simplicity. They are explained nevertheless. It can be seen that ΔCoVaR, as defined in section 2.2 with q=0.99, is regressed on IR as the main variable of analysis. ΔCoVaR is measured using two techniques leading to four different specifications s: A GARCH(1,1) approach (GARCH) and a backward-looking rolling window technique with window length 13 (RW13W), 26 (RW26W) and 52 (RW52W) weeks. The features, strengths and weaknesses of both techniques are discussed in sections 2.2 and 2.3. Profitability (PRO) and the share of non-interest income as fraction of total assets (NII) are included as variables capturing the respective channels discussed in section 3. Additionally, the share of net interest income as fraction of total assets (II) is added as explanatory variable. Moreover, the standard deviation of the ratio of NII to II over all institutions in the system for each point in time (SD(NII/II)) is included. This measure is used to assess the scattering of the relative share of NII compared to II in the system and thus to evaluate to which degree the financial system is diversified with respect to these two major income streams. The remaining variables are control variables and are largely taken from a related contribution by Brunnermeier et al. (2020, p.244) that relates non-interest income and systemic risk (see section 3.3). As in their regression model, the logarithm of total assets (LOG(A)), leverage (LEV), the market-to-book ratio (MTB), liquidity (LIQ) and nonperforming loans as fraction of total assets (NPL) are included. On top of that, one potential bias has to be ruled out: During financial crises, it is regularly the case that volatility and systemic risk are rather high and monetary policy rates are rather low due to expansionary monetary policy. To thus prevent spurious correlation between IR and ΔCoVaR, market volatility (VOL) is included additionally as control variable. As IR and SD(NII/II) but in contrast to all other variables, VOL varies only in the time series and not in the cross-section. There are four slightly different specifications u of VOL depending on the specification of ΔCoVaR. The GARCH(1,1) estimate calculates ΔCoVaR from its one week lagged realizations of volatility and the error term. It can thus be interpreted as a (more or less) contemporary point estimate of systemic risk. Consequently, VOL is measured at the same point in time as ΔCoVaR, i.e. by a reporting day (RD) approach. The rolling window estimates of ΔCoVaR, though, take into account equally all individual and system returns within the respective window length. For instance, in the RW26W specification, all return observations of the 26 weeks preceding t are included. Thus, their outcome is better interpreted as the 'averaged' systemic risk in the respective subsampling period. In accordance with the window length of the ΔCoVaR estimate, VOL is estimated by a 13 (AV13W), 26 (AV26W) or 52 (AV52W) backward-looking rolling average stock market variability, respectively.

In accordance with e.g. Brunnermeier et al. (2020) and Saunders et al. (2020), most explanatory variables are lagged relative to the ΔCoVaR measurement. This is a suited way to encounter endogeneity and reverse causality issues (Saunders et al., 2020, p.3). The lag length is denoted by k. The only variable that is not lagged is VOL. The rationale behind it is that ΔCoVaR can only be reasonably controlled for VOL if both are measured simultaneously. Lagging the relevant variables by one period with respect to the ΔCoVaR measurement however leads to different lag lengths k for the different specifications. For consistency, the lag is adjusted in such a way that the relevant variables are lagged by one quarter with respect to the beginning of the ΔCoVaR measurement. This results in a lag length k of 1, 2, 3 and 5 quarters for the GARCH, RW13W, RW26W and RW52W specification, respectively.

Finally, some technical features of the model have to be specified. The model has both a cross-sectional and time-series dimension. Thus, it is employed a within-estimator panel data model accounting for individual-fixed effects (e.g. Verbeek, 2012, pp.377-379). Technically, it is not possible to account for time-fixed effects due to missing cross-sectional variation of some variables. The described model builds the base of the channel methodology described in section 4.1.2.

4.1.2 Channels

Besides the methodology for identifying the overall relation between interest rates and systemic risk, suitable approaches for analysing its channels have to be found. As discussed in section 3, search for yield, profitability, non-interest income and the diversification of the financial system with respect to the two major income streams are analysed in the present paper. This section discusses and determines the econometric models to accomplish this.

The presence of search for yield can be tested by analysing whether a bank's ex-ante leverage drives the overall relation. This can be done by inserting an interaction term between IR and LEV into the original regression equation 10. Regarding the remaining potential channels, finding an appropriate econometric model is less intuitive. The reason is that in these cases, the variables of interest are not expected to be an ex-ante determinant with which the overall connection interacts. Thus, employing interaction terms is not a suitable approach. Instead, it is expected that IR and a third variable, e.g. PRO, are related and that the third variable is further related to ΔCoVaR. This means that a third variable works as an intermediate step in the overall relation. A technique that follows this logic is the instrumental variable approach that is for instance explained by Baltagi (2011, pp.263-271) and Verbeek (2012, pp.148-154). It reflects the idea that an instrumental variable is associated with an independent variable that in turn affects a dependent variable. However, the approach requires the so-called exclusion condition (Roberts and Whited, 2013, pp.511-513): There must be no other relation between the instrumental and dependent variable except through the independent variable. This assumption is very strict, not directly testable and not fulfilled in the present paper's research environment: The channels analysed are in no way mutually exclusive and could work at the same time. Additionally, other unobserved influences cannot be ruled out. However, a much better fitting approach is mediation analysis, introduced by Baron and Kenny (1986). It can be illustrated in its simple form by figure 2.

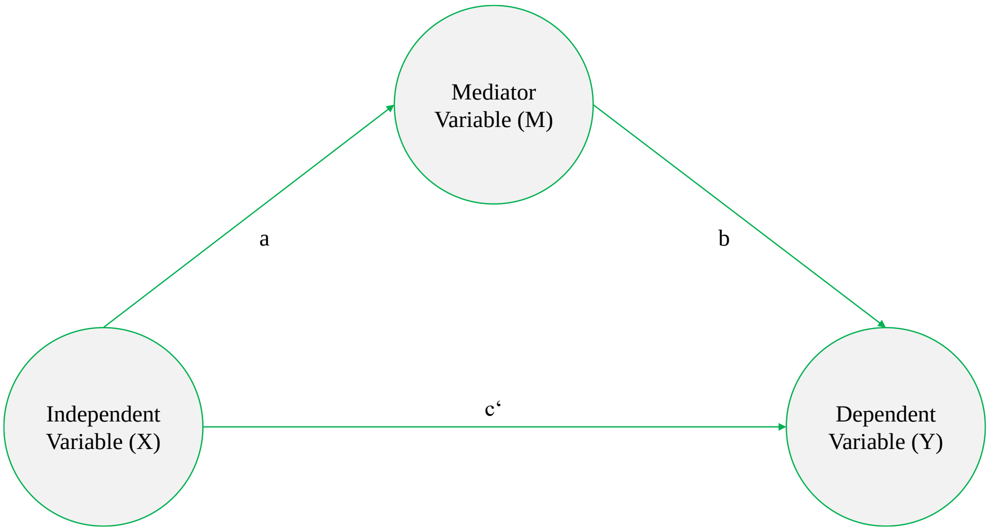

Figure 2: The principle of mediation analysis [Source: Own representation based on Hayes (2018, p.83)]

It is graphically shown that mediation analysis models the link between three variables (Hayes, 2018, pp.78-86): The independent variable (X), the dependent variable (Y) and a mediator variable (M). Mediation analysis investigates if a significant relationship between X and Y operates through a third variable M. In other words, it is investigated whether X is connected to M (path a) and if M is in turn connected to Y (path b). The relation between X and Y not operating through M is depicted as path c'. The total relation including the connection via a and b as well as c' is called c.

There is some discussion in the literature regarding which assumptions are to be fulfilled in order to apply mediation analysis. Baron and Kenny (1986, p.1177) require significant relationships between X and M (path a), M and Y (path b) and X and Y (c). This seems to be reasonable. It makes sense to test for the existence of an overall significant relation and each path before testing for a combined connection. However, Hayes (2018, pp.113-119) promotes a less restrictive approach where mediation analysis can still be conducted even if no significant evidence is found for path a or b. Besides significance assumptions, classical mediation models aim to establish evidence that X causally influences Y via M (Baron and Kenny, 1986, p.1176). To provide causal evidence, it is required that X precedes Y and that competing explanations can be ruled out (Hayes, 2018, p.79). In research settings that are not experimental, including the one in the present paper, the last point is very difficult to fulfill. Here it is central to mention that according to Hayes (2018, pp.81, 129-132), it is still feasible to estimate mediation models without interpreting their results strictly causally when causality-assumptions are violated. The research goal of the present paper is not to necessarily provide sound causal evidence. Thus, mediation analysis is an appropriate tool to analyse channels.

Technically, in order to analyse the indirect relation between X and Y via M, two regression models are needed as input (Hayes, 2018, p.82): The first one regressing M on X and the second one regressing Y on M and X. If there are additional control variables that are expected to drive Y, it has to be controlled for them in both models (Hayes, 2018, pp.122-129). Formally, this can be expressed by equations 11 and 12.

$$M = \alpha_M + aX + \sum_{n=1}^{N} \beta_M^n Z^n + \varepsilon_M \tag{11}$$

$$Y = \alpha_Y + c'X + bM + \sum_{n=1}^{N} \beta_Y^n Z^n + \varepsilon_Y \tag{12}$$

X, Y and M are the independent, dependent and mediator variable as in figure 2. The coefficients a, b and c’ represent the respective paths in figure 2 mathematically. Z^n is the nth of N control variables. β_M^n and β_Y^n are its respective coefficients. The intercept terms are α_M and α_Y. ε_M and ε_Y are the error terms.

Having estimated both models, the coefficients a and b from equations 11 and 12 are multiplied to calculate the indirect relation between X and Y via M. The sum of ab and the direct relation (c') between X and Y is equal to the total relation c between X and Y (Hayes, 2018, pp.83-86). This can be described formally by equation 13.

$$c = ab + c' \tag{13}$$

For the statistical inference, the standard error of ab, se_{ab}, is furthermore to be calculated. In accordance with Sobel (1982) and Baron and Kenny (1986, p.1177), it can be computed using the coefficients a and b and their respective standard errors, se_a and se_b as shown in equation 14.

$$se_{ab} = \sqrt{a^2 \times se_b^2 + b^2 \times se_a^2} \tag{14}$$

Having obtained the standard error, z-scores and p-values can be calculated as usual. With this, the model's statistical significance can be evaluated.

Last but not least, it shall be mentioned how the general concept of mediation analysis is applied to the specific research setting of the present paper. It is quite obvious that applying equation 12 results in the main model regressing ΔCoVaR on IR (equation 10). It serves as input for all mediation analyses in the following which guarantees good comparability between results. The second model needed as an input (equation 11) varies between the different mediation analyses. It uses the variable that represents the respective potential channel, e.g. PRO, as dependent variable (M) and all other variables (except ΔCoVaR) as independent variable. The results of the mediation models are presented and interpreted in sections 4.4.2 to 4.4.4.

4.2 Data

4.2.1 Discussion and Specification of the General Sample Features

Having specified the methodology, a suitable data sample has to be constructed. The regression presented in equation 10 relies on both a time series and a cross-sectional dimension. Therefore, panel data has to be employed. Here, three central aspects have to be considered: The sampling period, the country (group) and the definition of the institutions included.

First, the time period to be analysed is considered. It should cover some variation in the general interest level and the recent period of prolonged low interest rate after the GFC that fundamentally changed banks profit opportunities. However, distortions caused by the ongoing COVID-19 pandemic are deliberately excluded. Thus, analysing data from 2005 to 2019 seems to be a suitable approach. This means that the sampling period starts later than those in other papers that examine systemic risk empirically (e.g. Brunnermeier et al., 2020). Doing so fits better to the present paper's research goals.

Second, a geographic region has to be chosen. In principle, many countries have experienced a long time of low interest rates after the GFC. This paper focuses on the US. The general interest level there has a reasonable variation and has, in contrast to the Euro Area, experienced a slight increase in the recent years. Furthermore, the number of listed banks is large and quarterly accounting data is publicly available in regulatory reports.

Third, criteria have to be specified, according to which institutions are included in the data set. The present paper focuses on banks as a subgroup of financial institutions. An institution is a bank in the present paper's sense if it meets the following criteria: It files Consolidated Financial Statements for Holding Companies (FR Y-9C) reports at least in one quarter during the sampling period, it is classified by the Standard Industrial Classification (SIC) codes 60, 61 or 6712 on 3rd January 2005 and it still operates on 31st December 2019. Each part of the definition is discussed in the following. Requiring banks to file FR Y-9C reports is broadly applied in related literature (e.g.

Adrian and Brunnermeier, 2016; Brunnermeier et al., 2020). It guarantees that the respective bank operates in the US regulatory environment. Furthermore, FR Y-9C reports provide a broad set of useful accounting and regulatory variables on a quarterly basis (Board of Governors of the Federal Reserve System, 2021). The SIC-categorization of banks is taken from Adrian and Brunnermeier (2016, p.1738). It ensures that institutes included are listed and have at least in some form a traditional banking business model, i.e. collecting deposits and/or granting credits. This explicitly includes commercial banks, savings institutions and credit unions (United States Department of Labor, 2021). Non-bank financial institutions like insurance companies, venture capital companies and brokers are not included in the present paper's definition (United States Department of Labor, 2021). The SIC classification is assessed once in the beginning of the sampling period and not reassessed afterwards. However, it is required that the institution still operates (under whatever SIC code) in the end of the sampling period. This procedure is chosen for the following reasons. At first, limiting the dataset to institutions with continuous operations over the sampling period ensures that they are actually affected by changing interest rates. Institutions that start their operations during a period of prolonged low interest rates can be expected to build a business model that already accounts for this interest environment. Furthermore, for the assessment of systemic risk measures, it is extremely helpful to have a fixed financial system. This is the case because in this way it can be ensured that all stock returns can actually be used to calculate systemic risk measures and that no data points have to be dropped because an institute is temporarily not classified as being part of the system. Lastly, it is accounted for institutions that change their business model to one that would not initially fall under the present paper's banking definition. However, institutions going out of business because they are acquired by another company or due to bankruptcy are not included this way. It is assumed that acquisitions do not follow any systematic pattern and that bankruptcies occur very rarely. Thus, results are not expected to be systematically biased and it is assumed that advantages of having a continuous data set outweigh the potential risk of survivorship bias.

4.2.2 Data Sources and Data Management

Having defined the methodology and the overall properties of the data set, data sources for the variables described in section 4.1.1 have to be selected. For the estimation of ΔCoVaR, stock market data including prices and market capitalizations is needed. It is accessed on a daily frequency from the Center for Research in Security Prices (CRSP) via Wharton Research Data Services (WRDS) between 3rd January 2005 and 31st December 2019. For accounting variables, data is obtained on a quarterly basis from FR Y-9C regulatory reports via WRDS for 2005Q1 to 2019Q4.[2] To capture VOL, the present paper employs the Volatility Index (VIX) of the Chicago Board Options Exchange (CBOE). IR, the main variable, is measured by the overnight Effective Federal Funds Rate (FedFundR). For both VIX and FedFundR, historical data is obtained on a daily basis via Thomson Reuters Data Stream for the period between 3rd January 2005 and 31st December 2019.

In a first step, institutions classified by the SIC codes 60, 61 or 6712 on 3rd January 2005 are detected via WRDS. Hereby, the CRSP permanent number (PERMNO) is used as identifier. PERMNOs automatically account for changes in the company name or ticker during the sampling period. Then, the analysis is limited to institutions that still operate on 31st December 2019 under whatever SIC code (see reasoning in section 4.2.1). This is done by intersecting the banks detected on 3rd January 2005 with all operating companies contained in WRDS on 31st December 2019.[3] By this procedure, 252 institutions are identified, including those not filing FR Y-9C reports.

Daily stock market data is subsequently accessed for all these institutions. In line with Adrian and Brunnermeier (2016, p.1738), the data set is limited to ordinary common shares, whereas certificates like shares of beneficial interest or American Depository Receipts are excluded. This reduces the number of institutes included to 236. Shares with more than 50 missing prices in total

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[2] For technical reasons, FR Y-9C reports are imported between 2004Q4 and 2019Q4. 2004Q4 data is however deleted when setting up the final sample.
[3] Only three institutions in the sample do not anymore fulfill the banking definition (SIC codes 60, 61 or 6712) on 31st December 2019.

or more than 15 missing prices in a row are excluded from the data set. This affects 4 institutes leading to a set of 232 companies. All other missing values are corrected using linear interpolation. Consequently, daily prices are transformed to weekly returns. Returns are subsequently converted to negative (loss) returns by multiplying them with -1. Using weekly returns to calculate ΔCoVaR is in line with Adrian and Brunnermeier (2016). Along individual stock returns, weekly systemic loss returns are calculated as market-capitalization-weighted loss returns of individual stocks. Market capitalizations are one period lagged. This procedure is the same as the one applied by Brunnermeier et al. (2020, p.238). Having calculated individual and systemic returns, time-varying ΔCoVaR values are estimated for the four specifications (see section 4.1.1), in each case for q=0.99. In the end, this provides systemic risk data covering 782 weeks and 232 institutes.

In a next step, ΔCoVaR estimates have to be merged with regulatory accounting data from FR Y-9C reports, VIX and FedFundR data. Here, two challenges arise. First, different identifiers are used by the CRSP and in FR Y-9C reports. Second, the frequency of weekly ΔCoVaR estimates has to be synchronized with quarterly FR Y-9C data and daily VIX and FedFundR values. To encounter the first challenge, PERMNOs are first translated to CRSP permanent code (PERMCO)[4] and subsequently to Replication Server System Database Identifier (RSSD ID) using a translation table (Federal Reserve Bank of New York, 2020). Some missing matches can be complemented manually. All in all, 218 PERMNOs can be matched with RSSD IDs. For 199 institutions out of these, FR Y-9C reports are available at least at some point in the sampling time.[5] For them, relevant data is assessed from the reports. The second challenge is encountered by transferring all data with a frequency higher than quarterly accordingly. For each FR Y-9C reporting day, the latest available values of the FedFundR and for both types of ΔCoVaR estimates

[4] The link between PERMCO and PERMNO is almost one by one. In rare cases, a company with a certain PERMCO can issue two share classes with different PERMNOs.
[5] Unfortunately, missing data points cannot be simply replaced by other reports that US banks have to file as they differ substantially with respect to the frequency with which they have to be published and the variables included.

are assessed. For the VIX-values, the last available values as well as averages of the realizations are determined (see section 4.1.1).

The final unbalanced panel consists of data covering 199 banks in 60 quarters between 2005Q1 and 2019Q4. PERMNOs are used as identifier. It is ensured that companies with the same PERMNO but a changing RSSD ID are treated as one company. A detailed overview of the variables in equation 10 and their descriptions, calculations and sources is given in table A.1 in the appendix.

4.2.3 Descriptive Statistics

Summary statistics on relevant variables of the unbalanced panel employed are given in table 1.

Table 1: Summary statistics

Variable	No	Min	$Q_{25\%}$	Mean	$Q_{75\%}$	Max	SD
$\Delta CoVaR_{GARCH}$	11,940	-13.915	0.803	2.625	3.222	38.889	3.334
$\Delta CoVaR_{RW13W}$	11,741	-18.277	0.543	2.517	4.020	71.268	3.862
$\Delta CoVaR_{RW26W}$	11,542	-17.359	0.780	3.169	4.986	56.089	4.237
$\Delta CoVaR_{RW52W}$	11,144	-17.270	1.334	3.982	6.139	35.411	4.486
IR	11,940	0.040	0.090	1.416	2.407	5.340	1.736
PRO	10,166	-17.188	0.269	0.529	0.827	4.113	0.682
NII	10,166	-0.635	0.305	0.796	0.989	18.146	0.977
II	10,166	0.187	1.047	2.000	2.738	6.869	1.003
SD(NII/II)	11,940	47.522	54.465	56.993	60.434	66.948	4.644
LOG(A)	10,166	12.042	14.142	15.447	16.245	21.740	1.753
LEV	10,166	76.216	87.958	89.530	91.183	98.323	2.381
MTB	10,166	3.220	95.262	134.53	164.86	603.21	62.085
LIQ	10,166	1.665	17.170	25.856	31.585	84.772	12.484
NPL	10,166	0.000	1.012	1.457	1.672	9.192	0.796
VOL_{RD}	11,940	9.900	13.695	18.760	20.805	46.720	8.188
VOL_{AV13W}	11,741	10.263	13.606	18.524	20.673	58.856	8.197
VOL_{AV26W}	11,542	10.640	13.766	18.591	21.862	51.923	7.614
VOL_{AV52W}	11,144	11.132	13.979	18.748	22.281	40.617	6.854

Note: This table reports the number of observations (No), minimum (Min), 25% quantile ($Q_{25\%}$), mean, 75% quantile ($Q_{75\%}$), maximum (Max) and standard deviation (SD) of the variables in the main regression (equation 10). Indices are mostly dropped for simplicity.

The first aspect to be mentioned is that ΔCoVaR-values are on average substantially higher in this paper's data set than in other papers (e.g. 1,17% in Adrian and Brunnermeier, 2016, p.1720 or 1.02% in Brunnermeier et al., 2020, p.242). A potential reason why this might be the case is that the financial system in the present paper is defined much tighter than in the literature contributions named above. When the financial system has less constituents, the relative importance of one can be expected to be higher. Furthermore, when the financial system comprises companies that operate in businesses other than banking, systemic risk originating from one institution can be expected to be lower due to diversification effects. IR is between 0.04% and 5.34% which means a satisfactory range of variation for analysing the relationship with systemic risk. All other variables are within an expected value range such that, in accordance with Brunnermeier et al. (2020), winsorization is not necessary. The time series of the cross-sectional average of the four ΔCoVaR measures are graphically depicted in figure A.1 in the appendix. It can be seen that the measures are especially high during times of high economic stress with a peak during the GFC.

Additionally, the IR time series is graphically depicted in the appendix (figure A.2). It is rising from 2005 onwards to its highest value before the GFC, decreasing sharply thereafter. Consequently, it is constantly low between 2009 and 2016 before gradually increasing thereafter.

Lastly, the correlation matrix is reported in the appendix (table A.2). All pairwise correlations are below 60% in absolute terms. This indicates that multicollinearity is not a problem in the present analysis.

4.3 Overall Relation – Results and Discussion

4.3.1 Main Results and Interpretation

Table 2 reports the results of the main model regressing ΔCoVaR on IR and various channel and control variables.

Table 2: Regression of systemic risk on interest rates (no seasonal adjustment)

	Dependent variable: $\Delta CoVaR^{j\|i}_{0.99,t,s}$			
s =	GARCH	RW13W	RW26W	RW52W
k=	1	2	3	5
IR_{t-k}	-0.1083*** (0.0210)	-0.0857*** (0.0294)	-0.0410 (0.0325)	-0.1777*** (0.0351)
PRO^{i}_{t-k}	-0.1929*** (0.0457)	0.0828 (0.0637)	-0.0328 (0.0692)	-0.0419 (0.0704)
NII^{i}_{t-k}	0.0990** (0.0496)	-0.0755 (0.0694)	0.0683 (0.0755)	-0.0169 (0.0786)
II^{i}_{t-k}	0.4186*** (0.0324)	-0.1834*** (0.0452)	0.0719 (0.0493)	0.2225*** (0.0508)
$SD(NII/II)_{t-k}$	-0.0778*** (0.0056)	-0.0230*** (0.0079)	-0.0220** (0.0087)	-0.1113*** (0.0091)
$LOG(A)^{i}_{t-k}$	0.3034*** (0.0779)	1.0780*** (0.1111)	1.8433*** (0.1239)	2.1108*** (0.1338)
LEV^{i}_{t-k}	0.0047 (0.0179)	-0.0469* (0.0253)	-0.1302*** (0.0278)	-0.1477*** (0.0288)
MTB^{i}_{t-k}	0.0024*** (0.0008)	0.0063*** (0.0011)	0.0115*** (0.0012)	0.0163*** (0.0012)
LIQ^{i}_{t-k}	0.0005 (0.0042)	-0.0088 (0.0059)	0.0075 (0.0065)	0.0087 (0.0067)
NPL^{i}_{t-k}	-0.3816*** (0.0497)	-0.0923 (0.0695)	0.0982 (0.0759)	-0.0400 (0.0778)
$VOL_{t,RD}$	0.2221*** (0.0034)			
$VOL_{t,AV13W}$		0.1947*** (0.0048)		
$VOL_{t,AV26W}$			0.2334*** (0.0058)	
$VOL_{t,AV52W}$				0.2546*** (0.0070)
Observations	10,024	9,882	9,740	9,456
R^2	0.4015	0.1805	0.1796	0.2096
Adjusted R^2	0.3889	0.1631	0.1619	0.1920
F Statistic	599***	194***	190***	223***

Note: This table reports the coefficients of four regression models with ΔCoVaR as dependent variable in different specifications (equation 10). Standard errors are given in parentheses. *, ** and *** correspond to a p-value below 0.1, 0.05 and 0.01, respectively.

All four models estimated are overall significant as expressed by high F statistics. In the GARCH specification, 40% of the variation in ΔCoVaR can be explained by the included variables. For the rolling window specifications,

R^2 lies roughly between 18% and 21% which is significantly lower as in the GARCH case but still indicates some explanatory power. The number of observations decreases monotonically from the first to the fourth model. This is due to the fact that for higher window lengths, estimates for ΔCoVaR are available from a later period in the sample.

It is started by interpreting the results of the main variable of interest, namely IR. The relation between IR and ΔCoVaR is negative in all models and significant at a 1% level in three of them. A decrease in IR of one percentage point is related to an increase in ΔCoVaR between 0.09 and 0.18 percentage points, depending on the specification. The economic magnitude is thus moderate yet significant. All in all, this leads to the conclusion that H1 can be accepted. The finding is in line with literature discussed in sections 1 and 3.1.2 and serves as starting point for the channel analysis. Strictly speaking, mediation analysis requires the relation between IR and ΔCoVaR to be significant when the mediator variables are not part of the model. Table A.3 in the appendix shows that this is given when dropping the respective variables.

PRO is found to be significantly negatively related to ΔCoVaR only in the GARCH specification. Because GARCH is a punctual ΔCoVaR measure at t whereas the other approaches cover time periods starting at t, this could be interpreted in a way that PRO is only in the short run related to ΔCoVaR. NII is positively and significantly related to ΔCoVaR only in the GARCH specification. This provides moderate to weak support of the findings by Brunnermeier et al. (2020) but is not completely contrary to them. The results with respect to II are very heterogeneous with respect to sign and significance. SD(NII/II) is negatively and significantly related to ΔCoVaR which is not in line with the predicted sign (see section 3.4). In section 4.4, these results are reconsidered in the channel analysis.

Finally, the remaining control variables are interpreted. For LOG(A), a positive and significant relation to ΔCoVaR is found in all specifications. Banks' size is linked to higher systemic risk what makes sense from an intuitive point of view. Brunnermeier et al. (2020) find no significant relation between

LOG(A) and ΔCoVaR but a significantly positive one between LOG(A) and MES. MTB and ΔCoVaR are significantly and positively connected in all specifications meaning that banks with a higher market-to-book valuation exert higher systemic risk. Liquidity is found to be insignificantly related to ΔCoVaR whereas Brunnermeier et al. (2020) find a negative and significant relation. NPL is only in the GARCH specification negatively related to systemic risk. VOL is positively and highly significantly related to ΔCoVaR in all specifications. This shows that ΔCoVaR is largely driven by overall market volatility. Partial differences between the findings of the present paper and the results of Brunnermeier et al. (2020) might be driven to a large part by the fact that the two papers employ data that differs substantially in different aspects. Specifically, Brunnermeier et al. (2020) employ a longer sample and a wider definition with respect to the institutions included. In section 4.3.2, the findings of the main model are checked for their robustness.

4.3.2 Robustness Checks

This section checks the results found in section 4.3.1 for robustness with respect to statistical as well as economic assumptions. In section 4.2.3, multicollinearity is ruled out by showing that pairwise correlations are relatively low. However, two other violations of the linear regression assumptions are frequently found in economic panel data: Heteroscedasticity and autocorrelation. Therefore, it is tested for the presence of both violations. Heteroscedasticity is tested for by conducting the Breusch-Pagan test (Breusch and Pagan, 1979). The test results are reported in table A.4 in the appendix. It is provided highly significant evidence for heteroscedasticity being present in all model specifications. The model is furthermore tested for the presence of autocorrelation by employing the Durbin-Watson test (Durbin and Watson, 1950). Results are reported in table A.5 in the appendix. They strongly suggest that autocorrelation is present in three of four model specifications. This means that it has to be ensured that the test statistics reported in table 2 are robust with respect to both heteroscedasticity and autocorrelation. This can be done by estimating heteroscedasticity- and autocorrelation-consistent standard errors as suggested by Arellano (1987) and Long and Ervin (2000). The application to the model of section 4.3.1 is shown in table A.6 in the appendix. It is shown that the coefficients relating IR to ΔCoVaR are still significant in three of four specifications. Thus, the main relation between these two variables seems to be robust with respect to heteroscedasticity and autocorrelation. Coefficients of SD(NII/II) are furthermore robust. However, none of the coefficients relating PRO and NII to ΔCoVaR are significant. This supports the already weak evidence on these two variables as ΔCoVaR determinants from the main model.

Next, two economic assumptions of the main model are challenged. The first one is that the main model in section 4.3.1 implicitly assumes, in accordance with Brunnermeier et al. (2020), that there is no need to adjust for seasonality in explanatory variables. However, the cross-sectional averages of PRO, NII, II, and LEV are found to exhibit seasonal fluctuations (see figures A.3 to A.6 in the appendix) which might potentially lead to flawed results. As a consequence, for each institution, seasonally adjusted values (adj) for the mentioned variables are calculated and SD(NII/II) is recomputed accordingly. With these variables, the main model is re-estimated. The resulting seasonally-adjusted model is used in section 4.4 to check results with respect to channels for their robustness. The results are reported in table 3. It can be seen that the main result, i.e. the negative and significant relation between IR and ΔCoVaR, is qualitatively unchanged. Quantitatively, the link is slightly weaker in three and slightly stronger in one of the specifications. Results with respect to PROadj have not changed qualitatively. The evidence that NIIadj drives systemic risk is weak again. Only in one specification, the relation is significant but with the opposite sign as in the original specification. SD(NIIadj/IIadj) is significant in all specifications but with the opposite sign as in the prior main model. This is more in line with the theoretical predictions discussed in section 3.4.

Table 3: Regression of systemic risk on interest rates (seasonal adjustment)

	Dependent variable: $\Delta\mathrm{CoVaR}^{j\|i}_{0.99,t,s}$			
s =	GARCH	RW13W	RW26W	RW52W
k=	1	2	3	5
IR_{t-k}	-0.0817*** (0.0215)	-0.0697** (0.0296)	-0.0305 (0.0328)	-0.2021*** (0.0357)
$\mathrm{PROadj}^{i}_{t-k}$	-0.2675*** (0.0482)	0.0639 (0.0660)	-0.0636 (0.0716)	-0.0756 (0.0734)
$\mathrm{NIIadj}^{i}_{t-k}$	-0.0110 (0.0764)	-0.2571** (0.1051)	0.0356 (0.1143)	-0.1593 (0.1184)
$\mathrm{IIadj\%}^{i}_{t-k}$	-0.2288** (0.1090)	-0.1907 (0.1500)	0.2650 (0.1632)	0.0190 (0.1695)
$\mathrm{SD(NIIadj/IIadj)}_{t-k}$	0.0150*** (0.0028)	0.0074* (0.0038)	0.0088** (0.0042)	-0.0179*** (0.0042)
$\mathrm{LOG(A)}^{i}_{t-k}$	0.1600* (0.0829)	1.0425*** (0.1157)	1.8460*** (0.1289)	1.9433*** (0.1405)
$\mathrm{LEVadj}^{i}_{t-k}$	-0.0062 (0.0190)	-0.0534** (0.0263)	-0.1264*** (0.0289)	-0.1463*** (0.0301)
MTB^{i}_{t-k}	0.0029*** (0.0008)	0.0065*** (0.0011)	0.0112*** (0.0012)	0.0172*** (0.0013)
LIQ^{i}_{t-k}	-0.0168*** (0.0045)	-0.0095 (0.0063)	0.0089 (0.0069)	0.0004 (0.0072)
NPL^{i}_{t-k}	-0.2370*** (0.0523)	-0.0499 (0.0717)	0.1078 (0.0782)	0.0562 (0.0808)
$\mathrm{VOL}_{t,RD}$	0.2361*** (0.0034)			
$\mathrm{VOL}_{t,AV13W}$		0.2025*** (0.0047)		
$\mathrm{VOL}_{t,AV26W}$			0.2404*** (0.0056)	
$\mathrm{VOL}_{t,AV52W}$				0.2853*** (0.0066)
Observations	9,951	9,809	9,667	9,383
R^2	0.3766	0.1784	0.1792	0.1963
Adjusted R^2	0.3639	0.1614	0.1620	0.1789
F Statistic	536***	190***	188***	204***

Note: This table reports the coefficients of four regression models with ΔCoVaR as dependent variable in different specifications. Variables with the suffix ‘adj’ are seasonally adjusted. Standard errors are given in parentheses. *, ** and *** correspond to a p-value below 0.1, 0.05 and 0.01, respectively.

The second economic assumption to be challenged is the banking definition used in the main analysis. It is investigated, if the results hold for two different groups of banks, commercial banks in a stricter sense and all other banks. The sample employed in the main model is therefore divided into two subsamples: The first one comprises all banks that are classified as commercial banks by SIC codes 6020 to 6029 (United States Department of Labor, 2021) on 3rd January 2005 (153 institutes). The second group contains all other institutes (46 entities). The results for both groups are reported in the appendix (tables A.7 and A.8). They show an interesting effect of the division with respect to the IR variable. For the first group, a significant and negative relation between IR and ΔCoVaR is found in all specifications. The RW26W specification in which IR is insignificantly related to ΔCoVaR in the original model is now significant at a 10% level. Economically, the coefficients are of higher absolute magnitude than in the original specification. For the second group, the significant relation vanishes. The overall connection reported in the main model seems to be primarily driven by commercial banks whose systemic risk seems to be more strongly linked to the interest level. A reason for this might be that commercial banks offer a particularly broad product portfolio. Thus, it might be easier for them to switch to activities more profitable (and riskier) under low interest rates. For all other banks, their business activities might be more focused and strategic changes may be harder to conduct. However, the lack of a significant relation can also be due to the small sample of only 46 entities.

4.4 Channels – Results and Discussion

4.4.1 Search for Yield

In this section it is accessed how the relation between interest rates and systemic risk interacts with bank's leverage. This is done by including an interaction term between LEV and IR to the original model specification. Detailed results are given in the appendix (table A.9). Results with respect to control variables are largely unchanged. The new coefficients of IR and its interaction with LEV are of special interest, though. They are best interpreted when specific values of LEV are inserted and the resulting coefficient of IR given these LEV-values are calculated. This is done in table 4.

Table 4: Interaction between interest rates and leverage (no seasonal adjustment)

	Dependent variable: $\Delta\text{CoVaR}^{j\|i}_{0.99,t,s}$			
s=	GARCH	RW13W	RW26W	RW52W
k=	1	2	3	5
IR_{t-k}	-0.1184 (0.5811)	1.5521* (0.8108)	2.2462** (0.8853)	2.9060*** (0.9109)
$IR_{t-k} \times LEV^{i}_{t-k}$	0.0001 (0.0065)	-0.0182** (0.0090)	-0.0255*** (0.0098)	-0.0343*** (0.0101)
Overall coefficient for 25% quantile of LEV^{i}_{t-k}	-0.1085	-0.0520	0.0069	-0.1101
Overall coefficient for median of LEV^{i}_{t-k}	-0.1083	-0.0838	-0.0376	-0.1700
Overall coefficient for 75% quantile of LEV^{i}_{t-k}	-0.1081	-0.1108	-0.0752	-0.2207

Note: This table reports the coefficients of IR and of the interaction between IR and LEV of four regression models with ΔCoVaR as dependent variable in different specifications. Furthermore, the 25% quantile, median and 75% quantile of LEV are inserted into the interaction term and the resulting total coefficients for IR are reported. Standard errors are given in parentheses. *, ** and *** correspond to a p-value below 0.1, 0.05 and 0.01, respectively. Exact, i.e. unrounded, values are used for calculations.

The table shows that both the IR and the interaction coefficient are statistically significant at least at a 10% level in the rolling-window models but not in the GARCH-model. However, in the rolling window specifications, the economic effect is large: Increasing LEV from the 25th to the 75th quantile at minimum roughly doubles the overall IR coefficient in absolute terms. This can be seen as evidence all in all supportive of higher leverage enhancing systemic risk taking under low interest rates. Because leverage proxies for the degree of agency problems of a bank, this promotes the view that banks search for yield (see section 3.1). H2 is therefore supported.

However, the GARCH specification does not support H2. Thus, the model is checked for robustness with respect to seasonal adjustment of various variables, e.g. LEV. Regression results and the table calculating the coefficients for given LEVadj-values are given in the appendix (tables A.10 and A.11). The coefficients of IR and the interaction are statistically significant in all specifications. The economic effects of different LEVadj-values are similar to those of the previous model. The evidence for search for yield is supported.

4.4.2 Profitability

In this section, the role of profitability in the interest rate-systemic risk relation is analysed. Preliminary evidence from the main model does not speak in favour for the existence of a profitability channel. Higher PRO as measured by ROA is significantly connected with lower systemic risk in only one specification. All in all, this is not supporting H3b. However, it is still worth to conduct mediation analysis. The second regression model necessary is estimated. It regresses PRO on IR. The results are given in table A.12 the appendix. They show that in three specifications, IR is positively and at least at a 10% level significantly related to PRO. This evidence supports H3a but should not only be interpreted as technical step in order to do mediation analysis. It further bears an interesting side result: The positive relation between PRO and IR supports that low profitability indeed exists in a low interest rate environment. This side result can be seen as additional support for search for yield, because the effect exists due to profitability pressure. Both models are combined using mediation analysis. Table 5 reports the summary.

Table 5: Mediation analysis on profitability (no seasonal adjustment)

	Dependent variable: $\Delta CoVaR^{j\|i}_{0.99,t,s}$			
s=	GARCH	RW13W	RW26W	RW52W
k=	1	2	3	5
IR_{t-k} via PRO^{i}_{t-k}	-0.0018* (0.0010)	0.0007 (0.0007)	-0.0003 (0.0006)	-0.0002 (0.0004)
Magnitude relative to direct relation (in %)	1.64%	-0.67%	0.27%	0.18%

Note: This table reports the coefficient of the indirect relation between IR and ΔCoVaR in four specifications via PRO and its relative magnitude compared to the direct relation. Standard errors are given in parentheses. *, ** and *** correspond to a p-value below 0.1, 0.05 and 0.01, respectively. Exact, i.e. unrounded, values are used for calculations.

The indirect link, i.e. the dependence between IR and ΔCoVaR via PRO is statistically marginally significant only in the GARCH-specification. Here, an increase in IR by one percentage point reduces ΔCoVaR indirectly by 0.0018 percentage points via PRO. Indirect coefficients in the following sections can be interpreted analogously. Economically, this is less than 2% of the direct relation which can be seen as insignificant. H3c has to be rejected.

It is further tested for the robustness of the results. The indirect relation is re-estimated using the seasonally adjusted main model (see section 4.3.2) and a corresponding seasonally adjusted model regressing PROadj on IR. Summaries of the second model and the mediation analysis are found in the appendix (tables A.13 and A.14). Results, especially of the mediation analysis, do not change substantially. The only notable difference is that PROadj and IR are positively and significantly related in all four specifications. In summary, this section's evidence does not support that profitability works as a channel for the connection between interest rates and systemic risk.

4.4.3 Non-Interest Income

This section assesses if the overall relation between interest rates and systemic risk can be explained by non-interest income. Preliminary evidence indicates that such an explanation is unlikely. In the main model, NII is insignificantly related to ΔCoVaR in three of four specifications with the remaining significant coefficient not being robust (see section 4.3.2). H4b thus has to be rejected. The second input model for mediation analysis regresses NII on IR. Results are reported in the appendix (table A.15). The relation between NII and IR is (weakly) statistically significant in only one model. Thus, H4a cannot be supported. Not surprisingly, the indirect relation is insignificant in all specifications, as shown in table 6. This leads to the rejection of H4c.

Table 6: Mediation analysis on non-interest income (no seasonal adjustment)

	Dependent variable: $\Delta\mathrm{CoVaR}^{j\mid i}_{0.99,t,s}$			
s=	GARCH	RW13W	RW26W	RW52W
k=	1	2	3	5
IR_{t-k} via NII^{i}_{t-k}	-0.0006 (0.0005)	0.0005 (0.0006)	-0.0005 (0.0006)	0.0001 (0.0007)
Magnitude relative to direct relation (in %)	0.51%	-0.57%	1.11%	-0.08%

Note: This table reports the coefficient of the indirect relation between IR and ΔCoVaR in four specifications via NII and its relative magnitude compared to the direct relation. Standard errors are given in parentheses. *, ** and *** correspond to a p-value below 0.1, 0.05 and 0.01, respectively. Exact, i.e. unrounded, values are used for calculations.

The results are checked for their robustness when the model is partly seasonally adjusted. In this case, the relation between ΔCoVaR and NIIadj is significant in only one specification. In the corresponding model regressing NIIadj on IR, these variables are significantly and negatively related in all specifications (see table A.16 in the appendix). The mediation analysis employing both models is statistically significant in only one specification (see table A.17 in the appendix). The coefficient is positive, which is the opposite sign as in the total relation and of low economic magnitude. Thus, the evidence that the negative connection between IR and ΔCoVaR operates through NII is weak in the main model and the results are robust to seasonal adjustments.

4.4.4 Income Stream Diversification of the Financial System

This section analyses if the connection between interest rates and systemic risk operates via income diversification of the financial system. In the main model, SD(NII/II) and ΔCoVaR are negatively and significantly related. This is contrary to theoretical predictions according to which a positive relationship can be expected and not supporting H5b. The second input model for mediation analysis regresses SD(NII/II) on IR. Its results are reported in the appendix (table A.18). It is found that IR and SD(NII/II) are significantly and negatively related in three specifications which supports H5a. The results of the mediation analysis are reported in table 7.

Table 7: Mediation analysis on income stream diversification of the financial system (no seasonal adjustment)

	Dependent variable: $\Delta\mathrm{CoVaR}^{j\|i}_{0.99,t,s}$			
s=	GARCH	RW13W	RW26W	RW52W
k=	1	2	3	5
IR_{t-k} via $\mathrm{SD(NII/II)}_{t-k}$	0.0402*** (0.0041)	0.0087*** (0.0031)	0.0058** (0.0024)	-0.0116** (0.0045)
Magnitude relative to direct relation (in %)	-37.10%	-10.15%	-14.20%	6.51%

Note: This table reports the coefficient of the indirect relation between IR and ΔCoVaR in four specifications via SD(NII/II) and its relative magnitude compared to the direct relation. Standard errors are given in parentheses. *, ** and *** correspond to a p-value below 0.1, 0.05 and 0.01, respectively. Exact, i.e. unrounded, values are used for calculations.

The results have to be interpreted carefully. On the one hand, the indirect relation is found to be statistically significant in all four specifications with heterogeneous economic magnitude reaching from 6.51% to 37.10% in absolute terms. On the other hand, having a closer look at the coefficients puts doubt on the evidence of the channel analysed: The coefficients are positive in three of four specifications what is contrary to the negative main relation. Thus, the channel would have to be interpreted as offsetting the interest rate-systemic risk relation rather than transmitting it. In the only specification where the coefficient has a negative sign, the economic magnitude is rather weak. In total, H5c cannot be supported from an economic viewpoint.

A useful approach for checking these rather surprising results for their robustness is to seasonally adjust the input models for mediation analysis. In the seasonally adjusted main model, the relation between SD(NIIadj/IIadj) and ΔCoVaR is positive and significant in three of four specifications which is in line with predictions from existing literature. In the corresponding model regressing SD(NIIadj/IIadj) on IR, the coefficient of IR is negative in all specifications and significant in three of them (table A.19 in the appendix). The results of the mediation analysis are contrary to the original specification. In three of four models, the indirect relation between IR and ΔCoVaR via SD(NIIadj/IIadj) is negative and significant (table A.20 in the appendix). Furthermore, the economic magnitude is, in absolute terms, substantially lower in all specifications than in the model reported in table 7. This shows that results are highly dependent on the specification chosen and not robust. However, the results from the seasonally adjusted model show that the evidence in this paper does not exclude the existence of the income diversification channel. Though, the economic magnitude is moderate to low in all specifications. In summary, evidence can therefore be considered as speaking against a substantial negative risk-transmission between interest rates and systemic risk via income stream diversification of the financial system. However, as discussed in section 3.4, existing research on this channel is rather limited. This provides interesting future research opportunities with respect to income stream diversification, e.g. by employing other measures.

4.5 Final Discussion and Limitations

Finally, two natural limitations of the analysis in this section should be mentioned. First, endogeneity issues and reverse causality cannot be ruled out completely. Endogeneity in the present context means that the relation between IR and ΔCoVaR might be driven by a third variable that is not part of the model but correlated with IR. It is almost impossible to completely encounter this concern. However, with a large set of control variables, the problem can be partly alleviated. Reverse causality would be present if monetary policy was conducted in response to systemic risk of banks. However, it can be seen as more likely that IR drives ΔCoVaR than vice versa. Initially, in the present analysis, explanatory variables are lagged with respect to the ΔCoVaR-measurement and thus precede systemic risk (Saunders et al., 2020, p.3). Moreover, literature on individual risk taking supports an effect directed from interest rates to individual risk (e.g. Dell'Ariccia et al., 2017; Ioannidou et al., 2015). Finally, central banks can be assumed to consider a large set of economic indicators when setting monetary policy. Systemic risk might be one of them, but unlikely the sole or primary driver. Nevertheless, the present paper abstains from a strictly causal interpretation of its results, because endogeneity and reverse causality issues cannot be ruled out completely.

Second, there is one central limitation of the channel analysis. The results of the interaction-based model analysing search for yield are quite hard to compare with those from the mediation models of the other potential channels, even if they are based on the same main model. In mediation analysis, establishing an indirect relation that is both statistically and economically significant can be quite difficult. Since (in absolute terms small) coefficients are multiplied and since there are various determinants of systemic risk, the resulting coefficients of the indirect relation are in many cases very small, too. In contrast, establishing a significant interaction might be easier. However, the results of the present paper with respect to channels strongly support a statistically and economically significant role of LEV and thus search for yield whereas the results of all other channels are much weaker. Thus, it is not assumed that the evidence is only driven by different econometric models.

5 Conclusion

The present paper aims to answer two research questions empirically by employing panel data on the US banking sector between 2005 and 2019. First, it is studied if and under which sign monetary policy rates and banks’ systemic risk are related. Second, it is analysed through which channels the relationship detected operates. It is found that interest rates are negatively and significantly related to systemic risk in three of four model specifications when controlling for various other potential and actual systemic risk drivers. Robustness checks all in all support this finding but indicate that the relation is largely driven by commercial banks. With respect to channels, the present paper’s evidence speaks in favour of a search for yield explanation. This means that banks take excessive risk due to profitability pressure under low interest rates. Evidence does not support a role of profitability or non-interest income as channels in the overall relation. The evidence with respect to income stream diversification does not support a major role in the transmission.

The contribution of this paper to existing literature is twofold. On the one hand, it supplements existing studies by focusing on the relation between interest rates and banks’ systemic instead of individual risk. The view of individual risk-taking literature that low interest rates are risk enhancing can be supported. On the other hand, this paper provides a distinctive analysis of different channels through which the relation might operate. The results support that the search for yield effect that has been detected by other authors for individual risk also drives systemic risk in a low interest environment.

Excessive risk taking under a low interest environment can finally be expected to occur not only in the banking sector. Instead, other financial institutions like life insurance companies or pension funds might face similar pressures in their portfolios. Thus, transferring the present paper’s analysis to other financial branches could give interesting future research opportunities.

Appendix

Table A.1: Variable descriptions, calculations and sources

Variable	Description	Calculation	Source
$\Delta CoVaR_{GARCH}$	Systemic risk exerted by a bank on the financial system (q=99%), in %	Equation 6	Estimated using a GARCH(1,1) approach
$\Delta CoVaR_{RW13W}$	Systemic risk exerted by a bank on the financial system (q=99%), in %	Equation 6	Estimated using a 13 weeks backward looking rolling window approach
$\Delta CoVaR_{RW26W}$	Systemic risk exerted by a bank on the financial system (q=99%), in %	Equation 6	Estimated using a 26 weeks backward looking rolling window approach
$\Delta CoVaR_{RW52W}$	Systemic risk exerted by a bank on the financial system (q=99%), in %	Equation 6	Estimated using a 52 weeks backward looking rolling window approach
IR	Interest rate measured by the overnight Effective Federal Funds Rate, in %	NA	Thomson Reuters Data Stream
PRO	Profitability measured by return on assets (ROA), in %	BHCK4340/ BHCK2170	FR Y-9C reports, own calculation
NII	Total non-interest income/total assets, in %	BHCK4079/ BHCK2170	FR Y-9C reports, own calculation
II	Net interest income/total assets, in %	BHCK4074/ BHCK2170	FR Y-9C reports, own calculation
SD(NII/II)	Income diversification of the financial system with respect to non-interest and interest income, in %	Standard deviation of the ratio (BHCK4079/ BHCK2170)/ (BHCK4074/ BHCK2170)	FR Y-9C reports, own calculation
LOG(A)	Logarithm of total assets, in logarithmized US-Dollars	log(BHCK2170)	FR Y-9C reports, own calculation
LEV	(Total assets - total holding company equity capital)/total assets, in %	(BHCK2170-BHCK3210)/ BHCK2170	FR Y-9C reports, own calculation
MTB	Market equity/total holding company equity capital, in %	Market capitalization/ BHCK3210	CRSP; FR Y-9C reports, own calculation

Table A.1: Variable descriptions and sources (ctd.)

Variable	Description	Calculation	Source
LIQ	(Cash + held-to-maturity securities + available-for-sale debt securities + trading assets)/total assets, in %	(BHCK0081+ BHCK0395+ BHCK0397+ BHCK1754+ BHCK1773+ BHCK3545)/ BHCK2170	FR Y-9C reports, own calculation
NPL	Allowance for loan and lease losses/total loans and leases held for investment, in %	BHCK3123/ BHCKB528	FR Y-9C reports, own calculation
VOL_{RD}	Volatility measured by the CBOE Volatility Index (VIX)	Reporting day (latest available value)	Thomson Reuters Data Stream
VOL_{AV13W}	Volatility measured by the CBOE Volatility Index (VIX)	Average value of the past 13 weeks	Thomson Reuters Data Stream
VOL_{AV26W}	Volatility measured by the CBOE Volatility Index (VIX)	Average value of the past 26 weeks	Thomson Reuters Data Stream
VOL_{AV52W}	Volatility measured by the CBOE Volatility Index (VIX)	Average value of the past 52 weeks	Thomson Reuters Data Stream

Note: This table reports the descriptions, calculation and sources of relevant variables used in the empirical analysis of the present paper. Indices are mostly dropped for simplicity. Details of the variables accessed from FR Y-9C reports can be found in Board of Governors of the Federal Reserve System (2021).

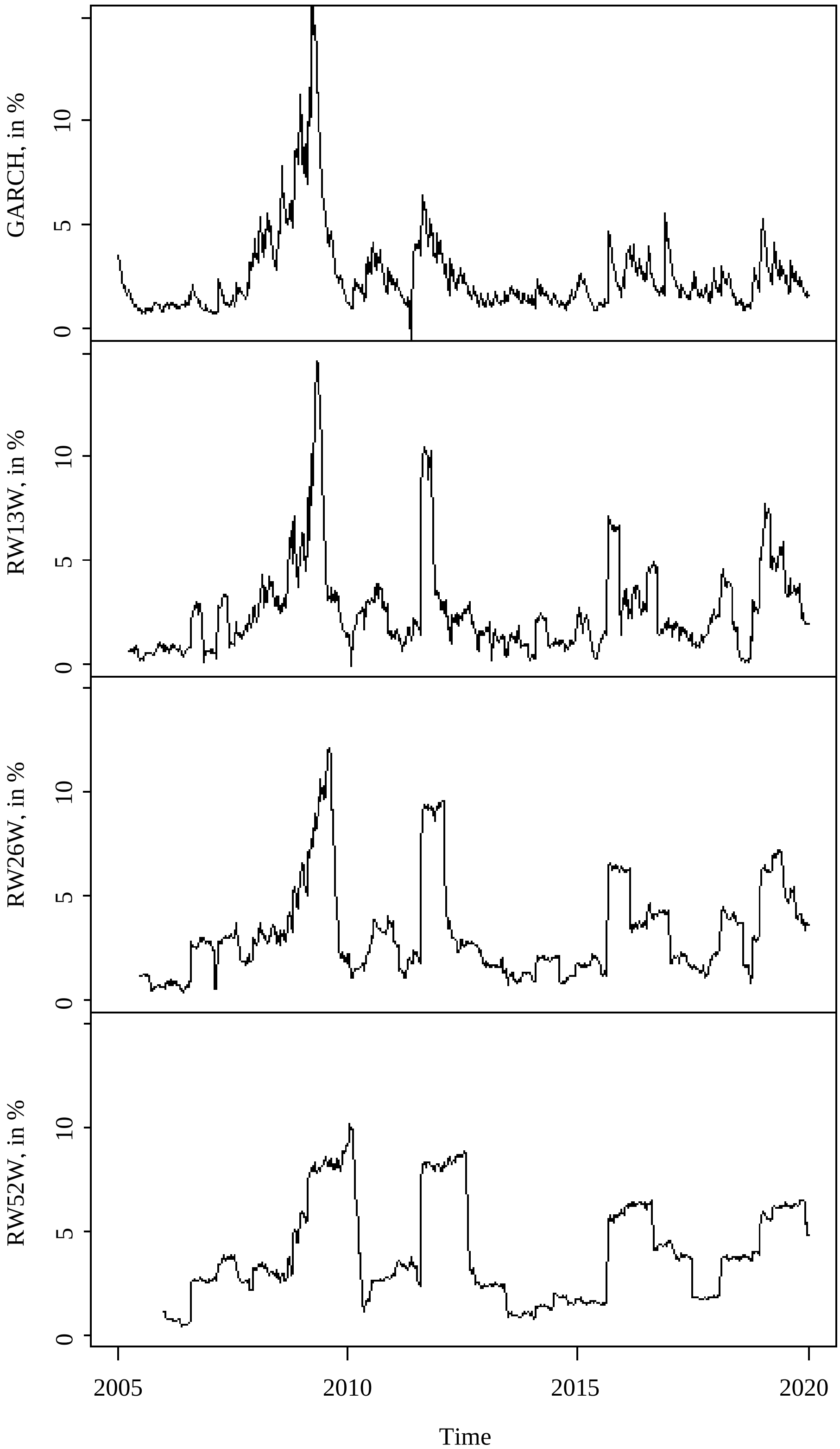

Figure A.1: Graphical representation of the Conditional Value at Risk time series in four specifications

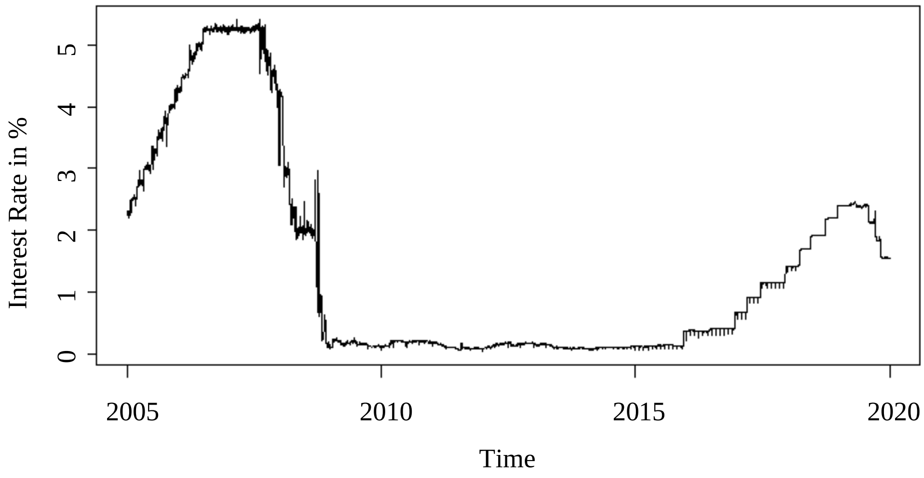

Figure A.2: Graphical representation of the overnight Effective Federal Funds Rate time series

Table A.2: Pairwise correlations of explanatory variables

	IR	PRO	NII	II	SD(NII/ II)	LOG(A)	LEV	MTB	LIQ	NPL	VOL_{RD}	VOL_{AV13W}	VOL_{AV26W}
PRO	0.12												
NII	0.00	0.29											
II	-0.03	0.31	0.28										
SD(NII/II)	-0.06	0.16	0.00	-0.03									
LOG(A)	-0.02	0.09	0.28	-0.13	0.02								
LEV	0.13	-0.20	-0.01	-0.11	-0.10	-0.21							
MTB	0.48	0.33	0.23	0.01	0.08	0.09	0.10						
LIQ	-0.11	0.04	0.10	-0.19	0.04	0.17	0.15	0.09					
NPL	-0.26	-0.26	0.08	0.11	-0.14	0.02	0.08	-0.31	0.05				
VOL_{RD}	-0.17	-0.15	0.02	0.05	-0.47	-0.05	0.12	-0.21	-0.02	0.16			
VOL_{AV13W}	-0.23	-0.18	0.04	0.09	-0.59	-0.06	0.12	-0.25	0.00	0.21	NA		
VOL_{AV26W}	-0.28	-0.22	0.01	0.00	-0.58	-0.07	0.12	-0.30	0.01	0.25	NA	NA	
VOL_{AV52W}	-0.37	-0.26	0.03	0.02	-0.47	-0.07	0.12	-0.36	0.03	0.34	NA	NA	NA

Note: This table reports the pairwise correlations between explanatory variables. Indices are mostly dropped for simplicity.

Table A.3: Regression of systemic risk on interest rates (no seasonal adjustment, reduced number of explanatory variables)

	Dependent variable: $\Delta\mathrm{CoVaR}^{j\|i}_{0.99,t,s}$			
s =	GARCH	RW13W	RW26W	RW52W
k=	1	2	3	5
IR_{t-k}	-0.0694*** (0.0210)	-0.0762*** (0.0292)	-0.0358 (0.0325)	-0.1896*** (0.0354)
II^{i}_{t-k}	0.4225*** (0.0264)	-0.1868*** (0.0364)	0.0932** (0.0396)	0.2164*** (0.0413)
$\mathrm{LOG(A)}^{i}_{t-k}$	0.2893*** (0.0785)	1.0766*** (0.1107)	1.8303*** (0.1235)	2.0329*** (0.1343)
LEV^{i}_{t-k}	0.0392** (0.0177)	-0.0473* (0.0247)	-0.1236*** (0.0271)	-0.1186*** (0.0283)
MTB^{i}_{t-k}	0.0013* (0.0008)	0.0062*** (0.0011)	0.0113*** (0.0012)	0.0165*** (0.0012)
LIQ^{i}_{t-k}	-0.0066 (0.0042)	-0.0096* (0.0058)	0.0061 (0.0064)	0.0026 (0.0066)
NPL^{i}_{t-k}	-0.2572*** (0.0487)	-0.0895 (0.0675)	0.1275* (0.0736)	0.0834 (0.0761)
$\mathrm{VOL}_{t,RD}$	0.2368*** (0.0032)			
$\mathrm{VOL}_{t,AV13W}$		0.1984*** (0.0045)		
$\mathrm{VOL}_{t,AV26W}$			0.2389*** (0.0054)	
$\mathrm{VOL}_{t,AV52W}$				0.2896*** (0.0064)
Observations	10,024	9,882	9,740	9,456
R^2	0.3880	0.1796	0.1789	0.1967
Adjusted R^2	0.3753	0.1624	0.1615	0.1791
F Statistic	778***	265***	260***	283***

Note: This table reports the coefficients of four regression models with ΔCoVaR as dependent variable in different specifications. Standard errors are given in parentheses. *, ** and *** correspond to a p-value below 0.1, 0.05 and 0.01, respectively.

Table A.4: Breusch-Pagan test for heteroscedasticity in the regression of systemic risk on interest rates (no seasonal adjustment)

	Dependent variable: $\Delta CoVaR^{j\|i}_{0.99,t,s}$			
s =	GARCH	RW13W	RW26W	RW52W
Degrees of freedom	11	11	11	11
Test statistic	1368.1***	373.3***	369.0***	655.1***

Note: This table reports the degrees of freedom, test statistics and p-values of the test of the null hypothesis of homoscedasticity according to Breusch and Pagan (1979). *, ** and *** correspond to a p-value below 0.1, 0.05 and 0.01, respectively.

Table A.5: Durbin-Watson test for autocorrelation in the regression of systemic risk on interest rates (no seasonal adjustment)

	Dependent variable: $\Delta CoVaR^{j\|i}_{0.99,t,s}$			
s =	GARCH	RW13W	RW26W	RW52W
Test statistic	1.3891***	1.9793	1.3910***	0.9122***

Note: This table reports the test statistics and p-values of the test of the null hypothesis of no autocorrelation according to Durbin and Watson (1950). *, ** and *** correspond to a p-value below 0.1, 0.05 and 0.01, respectively.

Table A.6: Regression of systemic risk on interest rates (no seasonal adjustment, robust standard errors)

	Dependent variable: $\Delta\text{CoVaR}^{j\|i}_{0.99,t,s}$			
s =	GARCH	RW13W	RW26W	RW52W
k=	1	2	3	5
IR_{t-k}	-0.1083*** (0.0214)	-0.0857*** (0.0289)	-0.0410 (0.0415)	-0.1777*** (0.0538)
PRO^i_{t-k}	-0.1929 (0.1239)	0.0828 (0.0925)	-0.0328 (0.1453)	-0.0419 (0.1903)
NII^i_{t-k}	0.0990 (0.0779)	-0.0755 (0.0605)	0.0683 (0.0823)	-0.0169 (0.0893)
II^i_{t-k}	0.4186*** (0.0455)	-0.1834*** (0.0438)	0.0719 (0.0500)	0.2225*** (0.0539)
SD(NII/II)_{t-k}	-0.0778*** (0.0045)	-0.0230*** (0.0071)	-0.0220** (0.0089)	-0.1113*** (0.0134)
LOG(A)^i_{t-k}	0.3034*** (0.0939)	1.0780*** (0.0999)	1.8433*** (0.1451)	2.1108*** (0.2147)
LEV^i_{t-k}	0.0047 (0.0222)	-0.0469* (0.0261)	-0.1302*** (0.0360)	-0.1477*** (0.0487)
MTB^i_{t-k}	0.0024** (0.0010)	0.0063*** (0.0013)	0.0115*** (0.0019)	0.0163*** (0.0023)
LIQ^i_{t-k}	0.0005 (0.0050)	-0.0088 (0.0061)	0.0075 (0.0083)	0.0087 (0.0108)
NPL^i_{t-k}	-0.3816*** (0.1132)	-0.0923 (0.0703)	0.0982 (0.1045)	-0.0400 (0.1346)
$\text{VOL}_{t,\text{RD}}$	0.2221*** (0.0097)			
$\text{VOL}_{t,\text{AV13W}}$		0.1947*** (0.0098)		
$\text{VOL}_{t,\text{AV26W}}$			0.2334*** (0.0128)	
$\text{VOL}_{t,\text{AV52W}}$				0.2546*** (0.0183)

Note: This table reports the coefficients of four regression models with ΔCoVaR as dependent variable in different specifications (equation 10). Standard errors are given in parentheses. They are calculated such that they are heteroscedasticity- and autocorrelation-consistent as suggested by Arellano (1987) and Long and Ervin (2000). *, ** and *** correspond to a p-value below 0.1, 0.05 and 0.01, respectively.

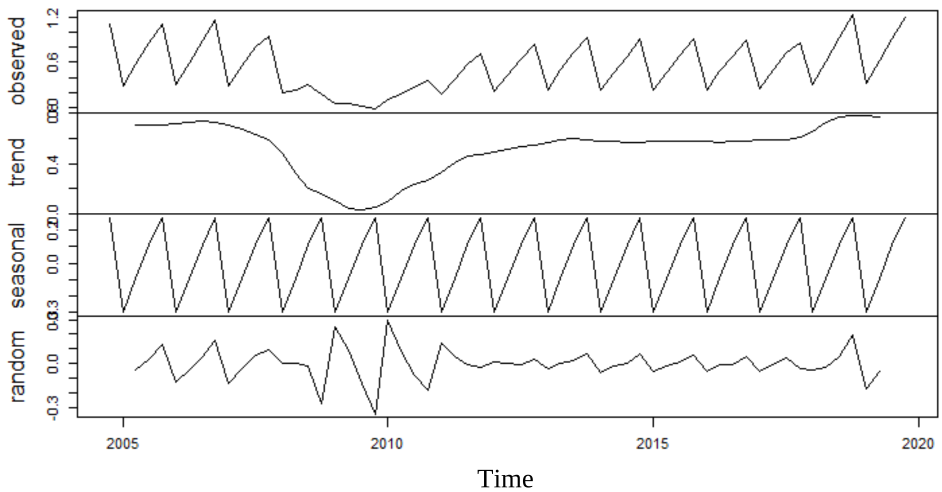

Figure A.3: Time series decomposition of the cross-sectional average of PRO

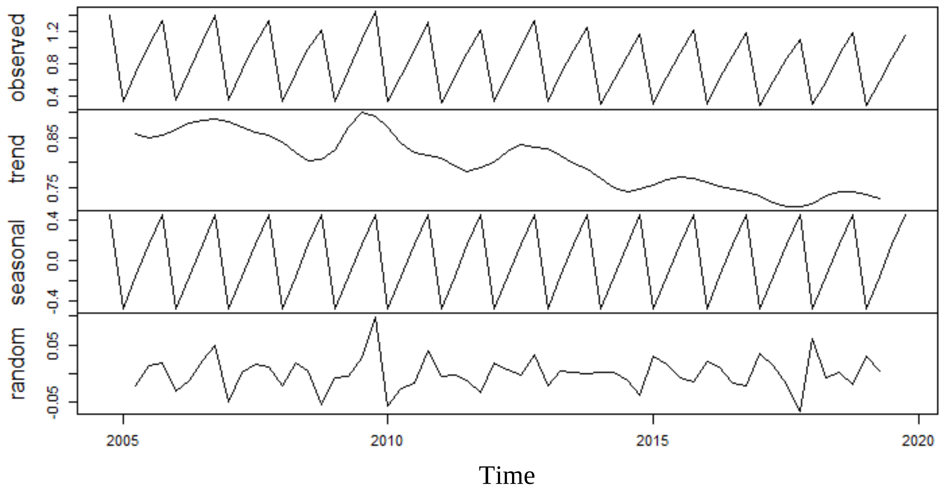

Figure A.4: Time series decomposition of the cross-sectional average of NII

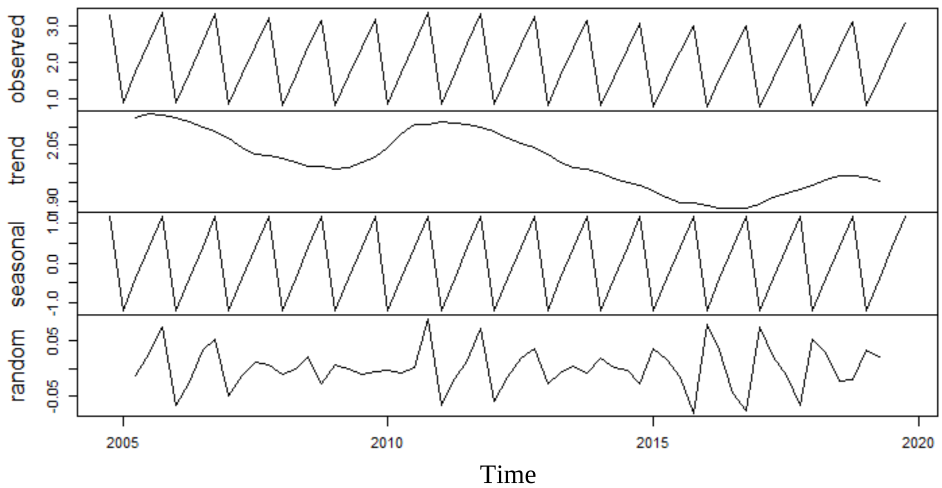

Figure A.5: Time series decomposition of the cross-sectional average of II

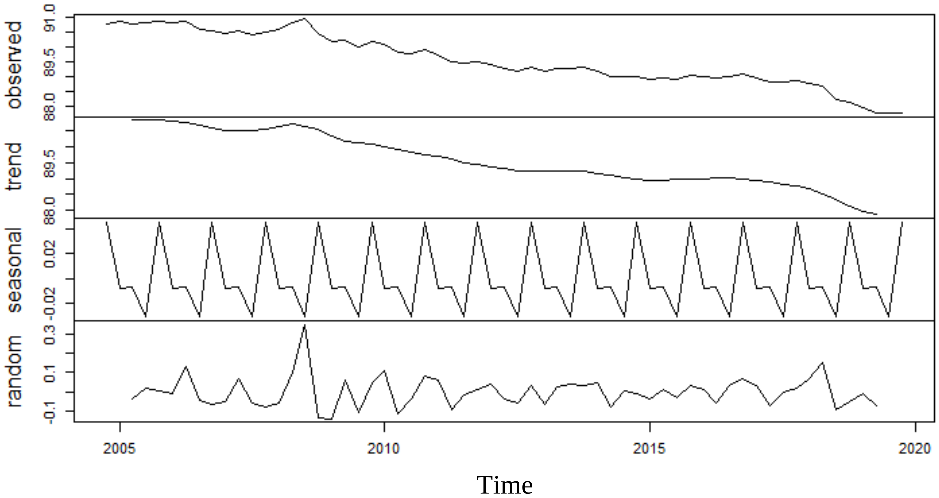

Figure A.6: Time series decomposition of the cross-sectional average of LEV

Table A.7: Regression of systemic risk on interest rates (no seasonal adjustment, only commercial banks)

	Dependent variable: $\Delta\mathrm{CoVaR}^{j\|i}_{0.99,t,s}$			
s =	GARCH	RW13W	RW26W	RW52W
k=	1	2	3	5
IR_{t-k}	-0.1136*** (0.0238)	-0.0990*** (0.0332)	-0.0651* (0.0365)	-0.1982*** (0.0396)
PRO^{i}_{t-k}	-0.0156 (0.0610)	0.1502* (0.0845)	0.1144 (0.0912)	0.1565* (0.0930)
NII^{i}_{t-k}	0.1218* (0.0738)	-0.1845* (0.1024)	0.1552 (0.1107)	0.0746 (0.1140)
II^{i}_{t-k}	0.3786*** (0.0413)	-0.1618*** (0.0572)	0.0298 (0.0619)	0.1267** (0.0635)
$\mathrm{SD(NII/II)}_{t-k}$	-0.0806*** (0.0063)	-0.0201** (0.0088)	-0.0239** (0.0096)	-0.1122*** (0.0102)
$\mathrm{LOG(A)}^{i}_{t-k}$	0.3466*** (0.0899)	1.1055*** (0.1274)	1.9051*** (0.1411)	2.1720*** (0.1524)
LEV^{i}_{t-k}	0.0303 (0.0214)	-0.0442 (0.0300)	-0.1458*** (0.0328)	-0.1764*** (0.0341)
MTB^{i}_{t-k}	0.0023** (0.0009)	0.0072*** (0.0012)	0.0127*** (0.0014)	0.0173*** (0.0014)
LIQ^{i}_{t-k}	0.0002 (0.0046)	-0.0063 (0.0065)	0.0126* (0.0071)	0.0129* (0.0073)
NPL^{i}_{t-k}	-0.3919*** (0.0582)	-0.0420 (0.0808)	0.1897** (0.0876)	0.0788 (0.0899)
$\mathrm{VOL}_{t,RD}$	0.2264*** (0.0037)			
$\mathrm{VOL}_{t,AV13W}$		0.1955*** (0.0052)		
$\mathrm{VOL}_{t,AV26W}$			0.2311*** (0.0063)	
$\mathrm{VOL}_{t,AV52W}$				0.2505*** (0.0076)
Observations	8,268	8,156	8,044	7,820
R^2	0.4063	0.1806	0.1787	0.2049
Adjusted R^2	0.3943	0.1639	0.1617	0.1880
F Statistic	504***	160***	156***	179***

Note: This table reports the coefficients of four regression models with ΔCoVaR as dependent variable in different specifications (equation 10). Standard errors are given in parentheses. *, ** and *** correspond to a p-value below 0.1, 0.05 and 0.01, respectively.

Table A.8: Regression of systemic risk on interest rates (no seasonal adjustment, all other banks)

	Dependent variable: $\Delta CoVaR^{j\|i}_{0.99,t,s}$			
s =	GARCH	RW13W	RW26W	RW52W
k=	1	2	3	5
IR_{t-k}	-0.0708 (0.0450)	-0.0340 (0.0669)	0.0950 (0.0762)	-0.0263 (0.0811)
PRO^{i}_{t-k}	-0.5151*** (0.0626)	-0.0057 (0.0929)	-0.1955* (0.1040)	-0.2453** (0.1043)
NII^{i}_{t-k}	0.0990* (0.0591)	0.0237 (0.0879)	-0.0227 (0.0986)	-0.1121 (0.1025)
II^{i}_{t-k}	0.4220*** (0.0547)	-0.1914** (0.0810)	0.0498 (0.0911)	0.3759*** (0.0935)
$SD(NII/II)_{t-k}$	-0.0745*** (0.0121)	-0.0428** (0.0181)	-0.0151 (0.0206)	-0.1109*** (0.0214)
$LOG(A)^{i}_{t-k}$	0.2732* (0.1492)	0.9466*** (0.2256)	1.6112*** (0.2595)	1.8763*** (0.2778)
LEV^{i}_{t-k}	-0.0630** (0.0303)	-0.0526 (0.0453)	-0.0754 (0.0511)	-0.0528 (0.0522)
MTB^{i}_{t-k}	0.0014 (0.0014)	0.0030 (0.0020)	0.0063*** (0.0023)	0.0114*** (0.0024)
LIQ^{i}_{t-k}	-0.0046 (0.0098)	-0.0232 (0.0147)	-0.0270 (0.0165)	-0.0221 (0.0169)
NPL^{i}_{t-k}	-0.2424*** (0.0937)	-0.1789 (0.1395)	-0.0201 (0.1572)	-0.1855 (0.1598)
$VOL_{t,RD}$	0.1895*** (0.0076)			
$VOL_{t,AV13W}$		0.1918*** (0.0119)		
$VOL_{t,AV26W}$			0.2526*** (0.0150)	
$VOL_{t,AV52W}$				0.2899*** (0.0179)
Observations	1,756	1,726	1,696	1,636
R^2	0.3926	0.1859	0.2031	0.2613
Adjusted R^2	0.3737	0.1601	0.1774	0.2366
F Statistic	100***	35***	38***	51***

Note: This table reports the coefficients of four regression models with ΔCoVaR as dependent variable in different specifications (equation 10). Standard errors are given in parentheses. *, ** and *** correspond to a p-value below 0.1, 0.05 and 0.01, respectively.

Table A.9: Regression of systemic risk on interest rates (no seasonal adjustment, including interaction between interest rates and leverage)

	Dependent variable: $\Delta\mathrm{CoVaR}^{j\|i}_{0.99,t,s}$			
s =	GARCH	RW13W	RW26W	RW52W
k=	1	2	3	5
IR_{t-k}	-0.1184 (0.5811)	1.5521* (0.8108)	2.2462** (0.8853)	2.9060*** (0.9109)
$\mathrm{IR}_{t-k} \times \mathrm{LEV}^{i}_{t-k}$	0.0001 (0.0065)	-0.0182** (0.0090)	-0.0255*** (0.0098)	-0.0343*** (0.0101)
PRO^{i}_{t-k}	-0.1929*** (0.0457)	0.0809 (0.0637)	-0.0357 (0.0692)	-0.0455 (0.0704)
NII^{i}_{t-k}	0.0991** (0.0497)	-0.0814 (0.0695)	0.0598 (0.0756)	-0.0298 (0.0786)
II^{i}_{t-k}	0.4186*** (0.0325)	-0.1816*** (0.0452)	0.0743 (0.0493)	0.2265*** (0.0508)
$\mathrm{SD(NII/II)}_{t-k}$	-0.0778*** (0.0056)	-0.0216*** (0.0079)	-0.0203** (0.0087)	-0.1092*** (0.0092)
$\mathrm{LOG(A)}^{i}_{t-k}$	0.3035*** (0.0782)	1.0592*** (0.1114)	1.8200*** (0.1242)	2.0919*** (0.1338)
LEV^{i}_{t-k}	0.0045 (0.0208)	-0.0175 (0.0292)	-0.0899*** (0.0319)	-0.0957*** (0.0327)
MTB^{i}_{t-k}	0.0024*** (0.0008)	0.0066*** (0.0011)	0.0119*** (0.0012)	0.0169*** (0.0012)
LIQ^{i}_{t-k}	0.0005 (0.0042)	-0.0086 (0.0059)	0.0078 (0.0065)	0.0091 (0.0067)
NPL^{i}_{t-k}	-0.3816*** (0.0497)	-0.0939 (0.0695)	0.0961 (0.0758)	-0.0421 (0.0778)
$\mathrm{VOL}_{t,RD}$	0.2221*** (0.0034)			
$\mathrm{VOL}_{t,AV13W}$		0.1946*** (0.0048)		
$\mathrm{VOL}_{t,AV26W}$			0.2333*** (0.0058)	
$\mathrm{VOL}_{t,AV52W}$				0.2545*** (0.0070)
Observations	10,024	9,882	9,740	9,456
R^2	0.4015	0.1809	0.1802	0.2106
Adjusted R^2	0.3888	0.1633	0.1624	0.1929
F Statistic	549***	178***	175***	206***

Note: This table reports the coefficients of four regression models with ΔCoVaR as dependent variable in different specifications (equation 10, augmented by an interaction term between IR and LEV). Standard errors are given in parentheses. *, ** and *** correspond to a p-value below 0.1, 0.05 and 0.01, respectively.

Table A.10: Regression of systemic risk on interest rates (seasonal adjustment, including interaction between interest rates and leverage)

	Dependent variable: $\Delta \mathrm{CoVaR}^{j\|i}_{0.99,t,s}$			
s =	GARCH	RW13W	RW26W	RW52W
k=	1	2	3	5
IR_{t-k}	1.0215* (0.5968)	1.9458** (0.8163)	2.4077*** (0.8901)	3.5800*** (0.9236)
$\mathrm{IR}_{t-k} \times \mathrm{LEVadj}^{i}_{t-k}$	-0.0123* (0.0066)	-0.0225** (0.0091)	-0.0271*** (0.0099)	-0.0421*** (0.0103)
$\mathrm{PROadj}^{i}_{t-k}$	-0.2683*** (0.0482)	0.0624 (0.0660)	-0.0656 (0.0716)	-0.0786 (0.0734)
$\mathrm{NIIadj}^{i}_{t-k}$	-0.0220 (0.0766)	-0.2776*** (0.1054)	0.0107 (0.1146)	-0.1997* (0.1188)
$\mathrm{IIadj\%}^{i}_{t-k}$	-0.2419** (0.1093)	-0.2142 (0.1503)	0.2378 (0.1634)	-0.0182 (0.1696)
$\mathrm{SD(NIIadj/IIadj)}_{t-k}$	0.0153*** (0.0028)	0.0079** (0.0038)	0.0093** (0.0042)	-0.0171*** (0.0042)
$\mathrm{LOG(A)}^{i}_{t-k}$	0.1441* (0.0834)	1.0139*** (0.1163)	1.8145*** (0.1294)	1.9100*** (0.1406)
$\mathrm{LEVadj}^{i}_{t-k}$	0.0129 (0.0217)	-0.0187 (0.0298)	-0.0851*** (0.0325)	-0.0847** (0.0336)
MTB^{i}_{t-k}	0.0031*** (0.0008)	0.0069*** (0.0011)	0.0117*** (0.0012)	0.0179*** (0.0013)
LIQ^{i}_{t-k}	-0.0168*** (0.0045)	-0.0095 (0.0063)	0.0088 (0.0068)	0.0004 (0.0072)
NPL^{i}_{t-k}	-0.2367*** (0.0523)	-0.0493 (0.0717)	0.1086 (0.0781)	0.0580 (0.0807)
$\mathrm{VOL}_{t,RD}$	0.2359*** (0.0034)			
$\mathrm{VOL}_{t,AV13W}$		0.2023*** (0.0047)		
$\mathrm{VOL}_{t,AV26W}$			0.2401*** (0.0056)	
$\mathrm{VOL}_{t,AV52W}$				0.2846*** (0.0066)
Observations	9,951	9,809	9,667	9,383
R^2	0.3769	0.1789	0.1799	0.1977
Adjusted R^2	0.3641	0.1618	0.1625	0.1803
F Statistic	491***	174***	173***	189***

Note: This table reports the coefficients of four regression models with ΔCoVaR as dependent variable in different specifications. Variables with the suffix 'adj' are seasonally adjusted. Standard errors are given in parentheses. *, ** and *** correspond to a p-value below 0.1, 0.05 and 0.01, respectively.

Table A.11: Interaction between interest rates and leverage (seasonal adjustment)

	Dependent variable: $\Delta\mathrm{CoVaR}^{j\|i}_{0.99,t,s}$			
s=	GARCH	RW13W	RW26W	RW52W
k=	1	2	3	5
IR_{t-k}	1.0215* (0.5968)	1.9458** (0.8163)	2.4077*** (0.8901)	3.5800*** (0.9236)
$\mathrm{IR}_{t-k} \times \mathrm{LEVadj}^{i}_{t-k}$	-0.0123* (0.0066)	-0.0225** (0.0091)	-0.0271*** (0.0099)	-0.0421** (0.0103)
Overall coefficient for 25% quantile of $\mathrm{LEVadj}^{i}_{t-k}$	-0.0594	-0.0288	0.0200	-0.1193
Overall coefficient for median of $\mathrm{LEVadj}^{i}_{t-k}$	-0.0811	-0.0684	-0.0279	-0.1935
Overall coefficient for 75% quantile of $\mathrm{LEVadj}^{i}_{t-k}$	-0.0990	-0.1011	-0.0674	-0.2547

Note: This table reports the coefficients of IR and of the interaction between IR and LEV of four regression models with ΔCoVaR as dependent variable in different specifications. Variables with the suffix 'adj' are seasonally adjusted. Furthermore, the 25% quantile, median and 75% quantile of LEV are inserted into the interaction term and the resulting total coefficients for IR are reported. Standard errors are given in parentheses. *, ** and *** correspond to a p-value below 0.1, 0.05 and 0.01, respectively. Exact, i.e. unrounded, values are used for calculations.

Table A.12: Regression of profitability on interest rates (no seasonal adjustment)

	Dependent variable: PRO^{i}_{t-k}			
Specification	(1)	(2)	(3)	(4)
k=	1	2	3	5
IR_{t-k}	0.0092** (0.0046)	0.0088* (0.0047)	0.0089* (0.0048)	0.0048 (0.0052)
NII^{i}_{t-k}	0.1716*** (0.0108)	0.1729*** (0.0109)	0.1729*** (0.0110)	0.1722*** (0.0115)
II^{i}_{t-k}	0.1834*** (0.0069)	0.1822*** (0.0070)	0.1813*** (0.0071)	0.1764*** (0.0073)
$SD(NII/II)_{t-k}$	0.0097*** (0.0012)	0.0096*** (0.0013)	0.0093*** (0.0013)	0.0103*** (0.0013)
$LOG(A)^{i}_{t-k}$	-0.0305* (0.0172)	-0.0430** (0.0177)	-0.0491*** (0.0183)	-0.0658*** (0.0197)
LEV^{i}_{t-k}	-0.0820*** (0.0039)	-0.0817*** (0.0039)	-0.0825*** (0.0040)	-0.0858*** (0.0042)
MTB^{i}_{t-k}	0.0024*** (0.0002)	0.0024*** (0.0002)	0.0025*** (0.0002)	0.0027*** (0.0002)
LIQ^{i}_{t-k}	0.0108*** (0.0009)	0.0108*** (0.0009)	0.0109*** (0.0009)	0.0114*** (0.0010)
NPL^{i}_{t-k}	-0.2330*** (0.0107)	-0.2320*** (0.0108)	-0.2326*** (0.0110)	-0.2305*** (0.0112)
$VOL_{t,RD}$	-0.0025*** (0.0007)			
$VOL_{t,AV13W}$		-0.0030*** (0.0008)		
$VOL_{t,AV26W}$			-0.0034*** (0.0009)	
$VOL_{t,AV52W}$				-0.0015 (0.0010)
Observations	10,024	9,882	9,740	9,456
R^2	0.3170	0.3145	0.3148	0.3029
Adjusted R^2	0.3027	0.3000	0.3000	0.2874
F Statistic	456***	444***	438***	402***

Note: This table reports the coefficients of four regression models with PRO as dependent variable. The models are used as an input for mediation analysis. Standard errors are given in parentheses. *, ** and *** correspond to a p-value below 0.1, 0.05 and 0.01, respectively.

Table A.13: Regression of profitability on interest rates (seasonal adjustment)

	Dependent variable: $PROadj^{i}_{t-k}$			
Specification	(1)	(2)	(3)	(4)
k=	1	2	3	5
IR_{t-k}	0.0096** (0.0045)	0.0102** (0.0046)	0.0110** (0.0047)	0.0102** (0.0051)
$NIIadj^{i}_{t-k}$	0.2388*** (0.0159)	0.2417*** (0.0161)	0.2426*** (0.0162)	0.2421*** (0.0166)
$IIadj\%^{i}_{t-k}$	0.2923*** (0.0227)	0.2899*** (0.0230)	0.2899*** (0.0232)	0.2808*** (0.0239)
$SD(NIIadj/IIadj)_{t-k}$	0.0033*** (0.0006)	0.0033*** (0.0006)	0.0032*** (0.0006)	0.0037*** (0.0006)
$LOG(A)^{i}_{t-k}$	0.0064 (0.0174)	-0.0055 (0.0179)	-0.0115 (0.0185)	-0.0245 (0.0200)
$LEVadj^{i}_{t-k}$	-0.0763*** (0.0039)	-0.0758*** (0.0040)	-0.0764*** (0.0041)	-0.0796*** (0.0042)
MTB^{i}_{t-k}	0.0022*** (0.0002)	0.0022*** (0.0002)	0.0022*** (0.0002)	0.0023*** (0.0002)
LIQ^{i}_{t-k}	0.0128*** (0.0009)	0.0127*** (0.0010)	0.0128*** (0.0010)	0.0131*** (0.0010)
NPL^{i}_{t-k}	-0.2487*** (0.0107)	-0.2467*** (0.0108)	-0.2479*** (0.0109)	-0.2453*** (0.0112)
$VOL_{t,RD}$	-0.0034*** (0.0007)			
$VOL_{t,AV13W}$		-0.0042*** (0.0007)		
$VOL_{t,AV26W}$			-0.0049*** (0.0008)	
$VOL_{t,AV52W}$				-0.0041*** (0.0009)
Observations	9,951	9,809	9,667	9,383
R^2	0.2336	0.2328	0.2326	0.2279
Adjusted R^2	0.2181	0.2170	0.2165	0.2113
F Statistic	297***	292***	287***	271***

Note: This table reports the coefficients of four regression models with PROadj as dependent variable. Variables with the suffix ‘adj’ are seasonally adjusted. The models are used as an input for mediation analysis. Standard errors are given in parentheses. *, ** and *** correspond to a p-value below 0.1, 0.05 and 0.01, respectively.

Table A.14: Mediation analysis on profitability (seasonal adjustment)

	Dependent variable: $\Delta\text{CoVaR}^{j\|i}_{0.99,t,s}$			
s=	GARCH	RW13W	RW26W	RW52W
k=	1	2	3	5
IR_{t-k} via PROadj^{i}_{t-k}	-0.0026** (0.0013)	0.0007 (0.0007)	-0.0007 (0.0008)	-0.0008 (0.0008)
Magnitude relative to direct relation (in %)	3.14%	-0.94%	2.29%	0.38%

Note: This table reports the coefficient of the indirect relation between IR and ΔCoVaR in four specifications via PROadj and its relative magnitude compared to the direct relation. Variables with the suffix ‘adj’ are seasonally adjusted. Standard errors are given in parentheses. *, ** and *** correspond to a p-value below 0.1, 0.05 and 0.01, respectively. Exact, i.e. unrounded, values are used for calculations.

Table A.15: Regression of non-interest income on interest rates (no seasonal adjustment)

	Dependent variable: NII^{i}_{t-k}			
Specification	(1)	(2)	(3)	(4)
k=	1	2	3	5
IR_{t-k}	-0.0056 (0.0043)	-0.0064 (0.0043)	-0.0067 (0.0044)	-0.0087* (0.0046)
PRO^{i}_{t-k}	0.1451*** (0.0092)	0.1456*** (0.0092)	0.1451*** (0.0093)	0.1384*** (0.0092)
II^{i}_{t-k}	0.3185*** (0.0058)	0.3188*** (0.0058)	0.3201*** (0.0058)	0.3196*** (0.0058)
$SD(NII/II)_{t-k}$	-0.0005 (0.0011)	0.0001 (0.0012)	0.0003 (0.0012)	0.0010 (0.0012)
$LOG(A)^{i}_{t-k}$	-0.1188*** (0.0158)	-0.1152*** (0.0162)	-0.1127*** (0.0168)	-0.1058*** (0.0177)
LEV^{i}_{t-k}	-0.0036 (0.0036)	-0.0050 (0.0037)	-0.0053 (0.0038)	-0.0063* (0.0038)
MTB^{i}_{t-k}	0.0005*** (0.0002)	0.0005*** (0.0002)	0.0005*** (0.0002)	0.0006*** (0.0002)
LIQ^{i}_{t-k}	0.0018** (0.0009)	0.0019** (0.0009)	0.0021** (0.0009)	0.0026*** (0.0009)
NPL^{i}_{t-k}	0.0292*** (0.0101)	0.0274*** (0.0102)	0.0250** (0.0103)	0.0203** (0.0103)
$VOL_{t,RD}$	0.0026*** (0.0007)			
$VOL_{t,AV13W}$		0.0036*** (0.0007)		
$VOL_{t,AV26W}$			0.0044*** (0.0008)	
$VOL_{t,AV52W}$				0.0060*** (0.0009)
Observations	10,024	9,882	9,740	9,456
R^2	0.3369	0.3391	0.3388	0.3388
Adjusted R^2	0.3231	0.3251	0.3246	0.3242
F Statistic	499***	496***	489***	474***

Note: This table reports the coefficients of four regression models with NII as dependent variable. The models are used as an input for mediation analysis. Standard errors are given in parentheses. *, ** and *** correspond to a p-value below 0.1, 0.05 and 0.01, respectively.

Table A.16: Regression of non-interest income on interest rates (seasonal adjustment)

	Dependent variable: $NIIadj^{i}_{t-k}$			
Specification	(1)	(2)	(3)	(4)
k=	1	2	3	5
IR_{t-k}	-0.0067** (0.0028)	-0.0080*** (0.0029)	-0.0092*** (0.0029)	-0.0124*** (0.0031)
$PROadj^{i}_{t-k}$	0.0950*** (0.0063)	0.0953*** (0.0063)	0.0953*** (0.0064)	0.0931*** (0.0064)
$IIadj\%^{i}_{t-k}$	-0.0754*** (0.0144)	-0.0769*** (0.0145)	-0.0774*** (0.0147)	-0.0778*** (0.0149)
$SD(NIIadj/IIadj)_{t-k}$	0.0013*** (0.0004)	0.0013*** (0.0004)	0.0014*** (0.0004)	0.0012*** (0.0004)
$LOG(A)^{i}_{t-k}$	-0.1873*** (0.0108)	-0.1860*** (0.0111)	-0.1864*** (0.0114)	-0.1885*** (0.0122)
$LEVadj^{i}_{t-k}$	-0.0256*** (0.0025)	-0.0264*** (0.0025)	-0.0270*** (0.0026)	-0.0270*** (0.0026)
MTB^{i}_{t-k}	0.0012*** (0.0001)	0.0012*** (0.0001)	0.0012*** (0.0001)	0.0012*** (0.0001)
LIQ^{i}_{t-k}	-0.0035*** (0.0006)	-0.0033*** (0.0006)	-0.0032*** (0.0006)	-0.0030*** (0.0006)
NPL^{i}_{t-k}	0.0673*** (0.0069)	0.0641*** (0.0069)	0.0632*** (0.0070)	0.0587*** (0.0071)
$VOL_{t,RD}$	0.0029*** (0.0004)			
$VOL_{t,AV13W}$		0.0034*** (0.0005)		
$VOL_{t,AV26W}$			0.0043*** (0.0005)	
$VOL_{t,AV52W}$				0.0050*** (0.0006)
Observations	9,951	9,809	9,667	9,383
R^2	0.0954	0.0948	0.0947	0.0926
Adjusted R^2	0.0770	0.0762	0.0758	0.0730
F Statistic	103***	101***	99***	94***

Note: This table reports the coefficients of four regression models with NIIadj as dependent variable. Variables with the suffix ‘adj’ are seasonally adjusted. The models are used as an input for mediation analysis. Standard errors are given in parentheses. *, ** and *** correspond to a p-value below 0.1, 0.05 and 0.01, respectively.

Table A.17: Mediation analysis on non-interest income (seasonal adjustment)

	Dependent variable: $\Delta\text{CoVaR}^{j\|i}_{0.99,t,s}$			
s=	GARCH	RW13W	RW26W	RW52W
k=	1	2	3	5
IR_{t-k} via seasonally adjusted NIIadj^{i}_{t-k}	0.0001 (0.0005)	0.0021* (0.0011)	-0.0003 (0.0011)	-0.0020 (0.0015)
Magnitude relative to direct relation (in %)	-0.09%	-2.95%	1.07%	-0.97%

Note: This table reports the coefficient of the indirect relation between IR and ΔCoVaR in four specifications via NIIadj and its relative magnitude compared to the direct relation. Variables with the suffix 'adj' are seasonally adjusted. Standard errors are given in parentheses. *, ** and *** correspond to a p-value below 0.1, 0.05 and 0.01, respectively. Exact, i.e. unrounded, values are used for calculations.

Table A.18: Regression of income stream diversification of the financial system on interest rates (no seasonal adjustment)

	Dependent variable: $SD(NII/II)_{t-k}$			
Specification	(1)	(2)	(3)	(4)
k=	1	2	3	5
IR_{t-k}	-0.5161*** (0.0372)	-0.3779*** (0.0377)	-0.2641*** (0.0382)	0.1040*** (0.0399)
PRO^{i}_{t-k}	0.6400*** (0.0816)	0.6234*** (0.0818)	0.5900*** (0.0813)	0.6091*** (0.0798)
NII^{i}_{t-k}	-0.0356 (0.0890)	0.0041 (0.0894)	0.0243 (0.0890)	0.0764 (0.0893)
II^{i}_{t-k}	-0.3425*** (0.0581)	-0.2965*** (0.0582)	-0.3741*** (0.0579)	-0.2585*** (0.0577)
$LOG(A)^{i}_{t-k}$	0.1745 (0.1396)	0.2820** (0.1430)	0.3519** (0.1459)	0.8033*** (0.1519)
LEV^{i}_{t-k}	-0.1918*** (0.0321)	-0.1808*** (0.0325)	-0.1707*** (0.0327)	-0.1670*** (0.0327)
MTB^{i}_{t-k}	0.0078*** (0.0014)	0.0059*** (0.0014)	0.0029** (0.0014)	-0.0042*** (0.0014)
LIQ^{i}_{t-k}	0.0578*** (0.0075)	0.0574*** (0.0076)	0.0493*** (0.0076)	0.0407*** (0.0076)
NPL^{i}_{t-k}	-0.8452*** (0.0886)	-0.8222*** (0.0891)	-0.8537*** (0.0889)	-0.8652*** (0.0880)
$VOL_{t,RD}$	-0.1749*** (0.0058)			
$VOL_{t,AV13W}$		-0.1859*** (0.0059)		
$VOL_{t,AV26W}$			-0.2274*** (0.0064)	
$VOL_{t,AV52W}$				-0.3121*** (0.0073)
Observations	10,024	9,882	9,740	9,456
R^2	0.1755	0.1857	0.2082	0.2597
Adjusted R^2	0.1583	0.1684	0.1911	0.2433
F Statistic	209***	221***	251***	325***

Note: This table reports the coefficients of four regression models with SD(NII/II) as dependent variable. The models are used as an input for mediation analysis. Standard errors are given in parentheses. *, ** and *** correspond to a p-value below 0.1, 0.05 and 0.01, respectively.

Table A.19: Regression of income stream diversification of the financial system on interest rates (seasonal adjustment)

	Dependent variable: $SD(NIIadj/IIadj)_{t-k}$			
Specification	(1)	(2)	(3)	(4)
k=	1	2	3	5
IR_{t-k}	-0.7831*** (0.0768)	-0.5512*** (0.0786)	-0.3811*** (0.0808)	-0.1035 (0.0884)
$PROadj^{i}_{t-k}$	0.9715*** (0.1730)	0.9909*** (0.1757)	0.9579*** (0.1765)	1.1096*** (0.1815)
$NIIadj^{i}_{t-k}$	0.9532*** (0.2746)	0.9597*** (0.2801)	1.0328*** (0.2819)	0.9533*** (0.2931)
$IIadj\%^{i}_{t-k}$	-1.4863*** (0.3917)	-1.3726*** (0.3999)	-1.2364*** (0.4028)	-1.1146*** (0.4195)
$LOG(A)^{i}_{t-k}$	-1.1311*** (0.2979)	-0.7399** (0.3086)	-0.5014 (0.3184)	0.1693 (0.3479)
$LEVadj^{i}_{t-k}$	0.0130 (0.0684)	-0.0096 (0.0701)	-0.0025 (0.0713)	-0.0850 (0.0745)
MTB^{i}_{t-k}	-0.0012 (0.0029)	-0.0021 (0.0029)	-0.0062** (0.0030)	-0.0073** (0.0032)
LIQ^{i}_{t-k}	-0.0122 (0.0163)	-0.0048 (0.0167)	-0.0098 (0.0169)	-0.00004 (0.0177)
NPL^{i}_{t-k}	-1.4233*** (0.1874)	-1.3761*** (0.1907)	-1.4398*** (0.1925)	-1.4097*** (0.1994)
$VOL_{t,RD}$	-0.3006*** (0.0118)			
$VOL_{t,AV13W}$		-0.2704*** (0.0122)		
$VOL_{t,AV26W}$			-0.3111*** (0.0135)	
$VOL_{t,AV52W}$				-0.2899*** (0.0160)
Observations	9,951	9,809	9,667	9,383
R^2	0.0919	0.0800	0.0853	0.0684
Adjusted R^2	0.0734	0.0610	0.0662	0.0483
F Statistic	99***	84***	88***	67***

Note: This table reports the coefficients of four regression models with SD(NIIadj/IIadj) as dependent variable. Variables with the suffix ‘adj’ are seasonally adjusted. The models are used as an input for mediation analysis. Standard errors are given in parentheses. *, ** and *** correspond to a p-value below 0.1, 0.05 and 0.01, respectively.

Table A.20: Mediation analysis on income stream diversification of the financial system (seasonal adjustment)

	Dependent variable: $\Delta \mathrm{CoVaR}^{j\|i}_{0.99,t,s}$			
s=	GARCH	RW13W	RW26W	RW52W
k=	1	2	3	5
IR_{t-k} via $\mathrm{SD(NIIadj/IIadj)}_{t-k}$	-0.0118*** (0.0025)	-0.0041* (0.0022)	-0.0034* (0.0017)	-0.0018 (0.0016)
Magnitude relative to direct relation (in %)	14.42%	5.84%	10.99%	-0.91%

Note: This table reports the coefficient of the indirect relation between IR and ΔCoVaR in four specifications via SD(NIIadj/IIadj) and its relative magnitude compared to the direct relation. Variables with the suffix 'adj' are seasonally adjusted. Standard errors are given in parentheses. *, ** and *** correspond to a p-value below 0.1, 0.05 and 0.01, respectively. Exact, i.e. unrounded, values are used for calculations.

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