Three Essays on Key Challenges for Modern Banking: Regulation, Interest Rate Hikes, and Cryptocurrencies

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I dedicate this dissertation to my parents—to my late mother, Heike Krettek, and to my father, Christian N. Krettek—whose unconditional support made this journey possible.

Düsseldorf in July 2025 Jonas Krettek

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List of Abbreviations

AG	Aktiengesellschaft
ANC	Anoncoin
AOCI	Accumulated other comprehensive income
apl. Prof.	außerplanmäßiger Professor
APT	Arbitrage Pricing Theory
Art.	Article
ASF	Available stable funding
BCBS	Basel Committee on Banking Supervision
BIS	Bank for International Settlements
bps	basis points
BTB	BitBar
BTC	Bitcoin
CAPM	Capital asset pricing model
CAR	Cumulative abnormal return
CARs	Cumulative abnormal returns
CC	Cryptocurrency
CCi30	Cryptocurrency index 30
CCs	Cryptocurrencies
CDS	Credit default swap
CDSs	Credit default swaps
CEO	Chief executive officer
CET	Central European Time
cf.	confer
CMAR	Cumulative market-adjusted return
COVID-19	Coronavirus disease 19
CPE	Cumulative prediction error
CRD	Capital Requirements Directive
CRIX	CRyptocurrency IndeX
CRM	Comprehensive risk measure
CRR	Capital Requirements Regulation
CSC	CasinoCoin
Def.	Definition
DEM	Deutsche eMark
DF	Deposit facility
DGC	Digitalcoin

Dist.	Distance
DLT	Distributed ledger technology
DMD	Diamond
DOGE	Dogecoin
doi	digital object identifier
Dr.	Doctor
Dr. rer. pol.	Doctor rerum politicarum
DTW	Dynamic time warping
EA-MPD	Euro Area Monetary Policy Event-Study Database
ECB	European Central Bank
e.g.	exempli gratia
EGRRCPA	Economic Growth, Regulatory Relief, and Consumer Protection Act
EMH	Efficient market hypothesis
Emp. Distr.	Empirical Distribution
Eq.	Equation
Eqs.	Equations
ES	Expected shortfall
esp.	especially
et al.	et alii/aliae
etc.	et cetera
EU	European Union
Eucl.	Euclidean
EUR	Euro
EURIBOR	Euro Interbank Offered Rate
ew	equally weighted
FDIC	Federal Deposit Insurance Corporation
Fed	Federal Reserve
FG	Forward guidance
Fig.	Figure
FLO	FLO
FOMC	Federal Open Market Committee
FRB	Federal Reserve Board
FRC	Freicoin
FRTB	Fundamental review of the trading book
FSB	Financial Stability Board
FTC	Feathercoin
FX	Foreign exchange

GARCH	Generalized autoregressive conditional heteroscedasticity
GFC	Global financial crisis
GIIPS	Greece, Italy, Ireland, Portugal, Spain
GLC	GoldCoin
GPT	Generative Pre-trained Transformer
G-SIB	Global systemically important bank
G-SIBs	Global systemically important banks
HQLA	High quality liquid assets
HVB	Hypovereinsbank
ID	Identifier
IDR	Incremental default risk
IDRC	Incremental default risk charge
i.e.	id est
IFABS	International Finance and Banking Society
IFC	Infinitecoin
IFRS	International Financial Reporting Standards
IG	Investment grade
IKB	Industriekreditbank
IRB	Internal ratings-based
IRBA	Internal ratings-based approach
IRC	Incremental risk charge
IS	Introductory statement
ISDA	International Swaps and Derivatives Association
LCR	Liquidity coverage ratio
LIBOR	London Interbank Offered Rate
LIBRO	Liquidity bounded risk–return optimization
LOCF	Last observation carried forward
LSAP	Large-scale asset purchase
LTC	Litecoin
M&A	Mergers & Acquisitions
Manh.	Manhattan
MEC	Megacoin
MLF	Marginal lending facility
MRO	Main refinancing operation
M.Sc.	Master of Science
MSCI	Morgan Stanley Capital International
mw	market-weighted

NMC	Namecoin
No.	Numero
NSFR	Net stable funding ratio
NVC	Novacoin
NXT	Nxt
Obs.	Observations
OCC	Office of the Comptroller of the Currency
OIS	Overnight index swap
OISs	Overnight index swaps
OLS	Ordinary least squares
OMNI	Omni
OTC	Over-the-counter
PCA	Principal component analysis
PD	Probability of default
pm	post meridiem
pp.	pages
PPC	Peercoin
QE	Quantitative easing
QRK	Quark
RBF	Radial basis function
RBFs	Radial basis functions
RCAP	Regulatory Consistency Assessment Program
RSF	Required stable funding
RWA	Risk-weighted assets
SBHC	Small bank holding company
SBHCs	Small bank holding companies
SD	Standard deviation
SDI	Stable distribution
Sec.	Section
SME	Small and medium-sized enterprise
SOFR	Secured Overnight Financing Rate
S&P	Standard and Poor's
sq.	squared
SSM	Single Supervisory Mechanism
SSRN	Social Science Research Network
STC	Simple, transparent and comparable
Tab.	Table

Tabs.	Tables
TAG	TagCoin
TRC	Terracoin
U.A.	Uitgesloten Aansprakelijkheid
UFJ	United Financial of Japan
UK	United Kingdom
Univ.-Prof.	Universitätsprofessor
U.S.	United States
USA	United States of America
USD	United States dollar
US-GAAP	United States Generally Accepted Accounting Principals
VaR	Value at risk
VIFs	Variance inflation factors
VIX	Volatility index
Vol.	Volume
WDC	WorldCoin
XPM	Primecoin
XRP	Ripple
ZET	Zetacoin

List of Symbols

Greek Alphabet

α	Tail parameter of the SDI
$\alpha^{E,r}$	Intercept in the regression model explaining $CAR_i(t_1,t_2)$ in response to ECB announcements
$\alpha^{E,s}$	Intercept in the regression model explaining $\Delta CAS_i(t_1,t_2)$ in response to ECB announcements
$\alpha^{F,r}$	Intercept in the regression model explaining $CAR_i(t_1,t_2)$ in response to Fed announcements
$\alpha^{F,s}$	Intercept in the regression model explaining $\Delta CAS_i(t_1,t_2)$ in response to Fed announcements
α^{r}	Intercept in the regression model explaining $CAR_{i,t}$ in response to regulatory events by the BCBS
α_{rb}	Regularization parameter in the context of RBFs
$\hat{\alpha}_i^r$	Estimated intercept from the market model regression for firm i (banks, insurers)
α^{s}	Intercept in the regression model explaining $\Delta CAS_{i,t}$ in response to regulatory events by the BCBS
$\hat{\alpha}_i^s$	Estimated intercept from the CDS factor model regression for firm i (banks, insurers)
$\hat{\alpha}_i^{si}$	Estimated intercept from the CDS single-index model regression for bank i
β	Skewness parameter of the SDI
$\beta_1^{E,r},\beta_2^{E,r},\beta_3^{E,r},\beta_4^{E,r}$	Coefficients for monetary policy shocks in the regression model explaining $CAR_i(t_1,t_2)$ in response to ECB announcements
$\beta_1^{E,s},\beta_2^{E,s},\beta_3^{E,s},\beta_4^{E,s}$	Coefficients for monetary policy shocks in the regression model explaining $\Delta CAS_i(t_1,t_2)$ in response to ECB announcements
$\beta_1^{F,r},\beta_2^{F,r}$	Coefficients for monetary policy shocks in the regression model explaining $CAR_i(t_1,t_2)$ in response to Fed announcements
$\beta_1^{F,s},\beta_2^{F,s}$	Coefficients for monetary policy shocks in the regression model explaining $\Delta CAS_i(t_1,t_2)$ in response to Fed announcements
$\boldsymbol{\beta}^{r\prime}$	Transposed vector of regression coefficients for bank-specific variables explaining $CAR_{i,t}$ in response to regulatory events by the BCBS
$\hat{\beta}_{1,i}^r$	Estimated coefficient from the market model regression for firm i (banks, insurers)

$\boldsymbol{\beta}^{s\prime}$	Transposed vector of regression coefficients for bank-specific variables explaining $\Delta CAS_{i,t}$ in response to regulatory events by the BCBS
$\hat{\beta}^s_{1,i}, \hat{\beta}^s_{2,i}, \hat{\beta}^s_{3,i}, \hat{\beta}^s_{4,i}$	Estimated coefficients from the CDS factor model regression for firm i (banks, insurers)
$\hat{\beta}^{si}_{1,i}$	Estimated coefficient from the CDS single-index model regression for bank i
γ	Scale parameter of the SDI
$\boldsymbol{\gamma}^{r\prime}$	Transposed vector of regression coefficients for country-specific variables explaining $CAR_{i,t}$ in response to regulatory events by the BCBS
$\boldsymbol{\gamma}^{s\prime}$	Transposed vector of regression coefficients for country-specific variables explaining $\Delta CAS_{i,t}$ in response to regulatory events by the BCBS
$\Delta AS_{i,t}$	Abnormal CDS spread change of firm i (banks, insurers) at time t
ΔCAS	Cumulative abnormal CDS spread change (banks, insurers)
$\overline{\Delta CAS}$	Average cumulative abnormal CDS spread change (banks, insurers)
$\overline{\Delta CAS}_c$	Average cumulative abnormal CDS spread change for credit risk events (banks only)
$\Delta CAS_{i,t}$	Cumulative abnormal CDS spread change of bank i in the event window (t_{-1}, t_{+1})
$\Delta CAS_i(t_1, t_2)$	Cumulative abnormal CDS spread change of firm i (banks, insurers) in the event window (t_1, t_2)
$\Delta CAS_{i,t,x}$	Cumulative abnormal CDS spread change of bank i in the event window (t_{-1}, t_{+1}) for risk category x
$\overline{\Delta CAS}_l$	Average cumulative abnormal CDS spread change for liquidity risk events (banks only)
$\overline{\Delta CAS}_m$	Average cumulative abnormal CDS spread change for market risk events (banks only)
$\overline{\Delta CAS}(t_1, t_2)$	Average cumulative abnormal CDS spread change in the event window (t_1, t_2) (banks, insurers)
$\Delta CMAS$	Cumulative market-adjusted CDS spread change (banks only)
$\overline{\Delta CMAS}_c$	Average cumulative market-adjusted CDS spread change for credit risk events (banks only)
$\Delta CMAS_{i,t}$	Cumulative market-adjusted CDS spread change of bank i in the event window (t_{-1}, t_{+1})
$\Delta CMAS_{i,t,x}$	Cumulative market-adjusted CDS spread change of bank i in the event window (t_{-1}, t_{+1}) for risk category x
$\overline{\Delta CMAS}_l$	Average cumulative market-adjusted CDS spread change for liquidity risk events (banks only)

$\overline{\Delta CMAS}_m$	Average cumulative market-adjusted CDS spread change for market risk events (banks only)
$\Delta MAS_{i,t}$	Market-adjusted CDS spread change of bank i at time t
$\Delta S_{index,t}$	Change in the CDS market index at time t
$\Delta S_{i,t}$	CDS spread change of firm i (banks, insurers) at time t
$\Delta Vola_t$	Change in the equity-implied volatility index at time t
δ	Location parameter of the SDI
$\boldsymbol{\delta}^{r\prime}$	Transposed vector of regression coefficients for control variables explaining $CAR_{i,t}$ in response to regulatory events by the BCBS
$\boldsymbol{\delta}^{s\prime}$	Transposed vector of regression coefficients for control variables explaining $\Delta CAS_{i,t}$ in response to regulatory events by the BCBS
ϵ^j	Matrix of idiosyncratic variations from PCA
$\epsilon^r_{i,t}$	Error term of bank i at time t in the regression explaining $CAR_{i,t}$ in response to regulatory events by the BCBS
$\epsilon^{*r}_{i,t}$	Abnormal return of firm i in t (generic notation)
$\epsilon^s_{i,t}$	Error term of bank i at time t in the regression explaining $\Delta CAS_{i,t}$ in response to regulatory events by the BCBS
$\epsilon^{*s}_{i,t}$	Abnormal CDS spread change of firm i in t (generic notation)
Λ^j	Matrix of factor loadings from PCA
$\boldsymbol{\lambda}$	Vector of ones
$\boldsymbol{\lambda}_{rb}$	Parameter vector in the context of RBFs
λ_w	Weighting coefficient in the context of RBFs
π	Mathematical constant
$\sum$	Sum sign
$\sum \overline{\Delta CAS}_c$	Sum of average cumulative abnormal CDS spread changes for credit risk regulation (banks only)
$\sum \overline{\Delta CAS}_{c\_ew}$	Sum of equally weighted average cumulative abnormal CDS spread changes for credit risk regulation (banks only)
$\sum \overline{\Delta CAS}_{c\_mw}$	Sum of market-weighted average cumulative abnormal CDS spread changes for credit risk regulation (banks only)
$\sum \overline{\Delta CAS}_l$	Sum of average cumulative abnormal CDS spread changes for liquidity risk regulation (banks only)
$\sum \overline{\Delta CAS}_{l\_ew}$	Sum of equally weighted average cumulative abnormal CDS spread changes for liquidity risk regulation (banks only)
$\sum \overline{\Delta CAS}_{l\_mw}$	Sum of market-weighted average cumulative abnormal CDS spread changes for liquidity risk regulation (banks only)

$\sum \overline{\Delta CAS}_m$	Sum of average cumulative abnormal CDS spread changes for market risk regulation (banks only)
$\sum \overline{\Delta CAS}_{m\_ew}$	Sum of equally weighted average cumulative abnormal CDS spread changes for market risk regulation (banks only)
$\sum \overline{\Delta CAS}_{m\_mw}$	Sum of market-weighted average cumulative abnormal CDS spread changes for market risk regulation (banks only)
$\sum \overline{\Delta CMAS}_c$	Sum of average cumulative market-adjusted CDS spread changes for credit risk regulation (banks only)
$\sum \overline{\Delta CMAS}_{c\_ew}$	Sum of equally weighted average cumulative market-adjusted CDS spread changes for credit risk regulation (banks only)
$\sum \overline{\Delta CMAS}_{c\_mw}$	Sum of market-weighted average cumulative market-adjusted CDS spread changes for credit risk regulation (banks only)
$\sum \overline{\Delta CMAS}_l$	Sum of average cumulative market-adjusted CDS spread changes for liquidity risk regulation (banks only)
$\sum \overline{\Delta CMAS}_{l\_ew}$	Sum of equally weighted average cumulative market-adjusted CDS spread changes for liquidity risk regulation (banks only)
$\sum \overline{\Delta CMAS}_{l\_mw}$	Sum of market-weighted average cumulative market-adjusted CDS spread changes for liquidity risk regulation (banks only)
$\sum \overline{\Delta CMAS}_m$	Sum of average cumulative market-adjusted CDS spread changes for market risk regulation (banks only)
$\sum \overline{\Delta CMAS}_{m\_ew}$	Sum of equally weighted average cumulative market-adjusted CDS spread changes for market risk regulation (banks only)
$\sum \overline{\Delta CMAS}_{m\_mw}$	Sum of market-weighted average cumulative market-adjusted CDS spread changes for market risk regulation (banks only)
$\sum \overline{CAR}_c$	Sum of average cumulative abnormal returns for credit risk regulation (banks only)
$\sum \overline{CAR}_{c\_ew}$	Sum of equally weighted average cumulative abnormal returns for credit risk regulation (banks only)
$\sum \overline{CAR}_{c\_mw}$	Sum of market-weighted average cumulative abnormal returns for credit risk regulation (banks only)
$\sum \overline{CAR}_l$	Sum of average cumulative abnormal returns for liquidity risk regulation (banks only)
$\sum \overline{CAR}_{l\_ew}$	Sum of equally weighted average cumulative abnormal returns for liquidity risk regulation (banks only)
$\sum \overline{CAR}_{l\_mw}$	Sum of market-weighted average cumulative abnormal returns for liquidity risk regulation (banks only)

$\sum \overline{CAR}_m$	Sum of average cumulative abnormal returns for market risk regulation (banks only)
$\sum \overline{CAR}_{m\_ew}$	Sum of equally weighted average cumulative abnormal returns for market risk regulation (banks only)
$\sum \overline{CAR}_{m\_mw}$	Sum of market-weighted average cumulative abnormal returns for market risk regulation (banks only)
$\sum \overline{CAR}_x$	Sum of average cumulative abnormal returns for risk category x (banks only)
$\sum \overline{CMAR}_c$	Sum of average cumulative market-adjusted returns for credit risk regulation (banks only)
$\sum \overline{CMAR}_{c\_ew}$	Sum of equally weighted average cumulative market-adjusted returns for credit risk regulation (banks only)
$\sum \overline{CMAR}_{c\_mw}$	Sum of market-weighted average cumulative market-adjusted returns for credit risk regulation (banks only)
$\sum \overline{CMAR}_l$	Sum of average cumulative market-adjusted returns for liquidity risk regulation (banks only)
$\sum \overline{CMAR}_{l\_ew}$	Sum of equally weighted average cumulative market-adjusted returns for liquidity risk regulation (banks only)
$\sum \overline{CMAR}_{l\_mw}$	Sum of market-weighted average cumulative market-adjusted returns for liquidity risk regulation (banks only)
$\sum \overline{CMAR}_m$	Sum of average cumulative market-adjusted returns for market risk regulation (banks only)
$\sum \overline{CMAR}_{m\_ew}$	Sum of equally weighted average cumulative market-adjusted returns for market risk regulation (banks only)
$\sum \overline{CMAR}_{m\_mw}$	Sum of market-weighted average cumulative market-adjusted returns for market risk regulation (banks only)
σ	Standard deviation of the SDI
$\sigma^2_{\epsilon_i}$	Variance of the error term from the estimation-period regression for firm i (banks, insurers)
σ^2_{rb}	Squared error between the modeled and sample values in the context of RBFs
$\hat{\sigma}_{\epsilon_i}$	Residual standard deviation from the estimation-period regression for firm i (banks, insurers)
τ_{uv}	Pairwise correlation of CC returns
$\hat{\tau}_{uv}$	Pairwise pre-smoothed correlation of CC returns modeled with RBFs
$\mathbf{\Phi}$	Matrix in the context of RBFs
ϕ_{ik}	Value of the k-th RBF at the sample point $\mathbf{x}_i$

ϕ_{iw}	Value of the w-th RBF at the sample point $\mathbf{x}_i$
$\phi(r)$	RBF of Gaussian type
Ω_t^r	Conditioning information for the normal return model at time t
Ω_t^s	Conditioning information for the normal CDS spread model at time t

Latin Alphabet

AFF_BANK_c	Dummy variable equal to 1 for U.S. banks not subject to the SBHC Policy Statement, and 0 otherwise
$AR_{i,t}$	Abnormal return of firm i (banks, insurers) at time t
a	Positive shape parameter of a RBF
$\mathbf{BANK}_{i,t}$	Vector of bank-specific variables of bank i at time t
$\mathbf{C}$	Core
$\overline{CAR}$	Average cumulative abnormal return (banks, insurers)
$\overline{CAR}_c$	Average cumulative abnormal return for credit risk events (banks only)
$CAR_{i,t}$	Cumulative abnormal return of bank i in the event window (t_{-1}, t_{+1})
$CAR_i(t_1, t_2)$	Cumulative abnormal return of firm i (banks, insurers) in the event window (t_1, t_2)
$CAR_{i,t,x}$	Cumulative abnormal return of bank i in the event window (t_{-1}, t_{+1}) for risk category x
$\overline{CAR}_l$	Average cumulative abnormal return for liquidity risk events (banks only)
$\overline{CAR}_m$	Average cumulative abnormal return for market risk events (banks only)
$\overline{CAR}_{m,e}$	Average cumulative abnormal return for market risk regulation and event e (banks only)
$\overline{CAR}(t_1, t_2)$	Average cumulative abnormal return in the event window (t_1, t_2) (banks, insurers)
$\overline{CAR}_{x,e}$	Average cumulative abnormal return for risk category x and event e (banks only)
$\overline{CMAR}_c$	Average cumulative market-adjusted return for credit risk events (banks only)
$CMAR_{i,t}$	Cumulative market-adjusted return of bank i in the event window (t_{-1}, t_{+1})
$CMAR_{i,t,x}$	Cumulative market-adjusted return of bank i in the event window (t_{-1}, t_{+1}) for risk category x
$\overline{CMAR}_l$	Average cumulative market-adjusted return for liquidity risk events (banks only)

$\overline{CMAR}_m$	Average cumulative market-adjusted return for market risk events (banks only)
$\mathbf{CONTROL}_{i,t}$	Vector of control variables of bank i at time t
COST_INC	Cost-to-income ratio
$\mathbf{COUNTRY}_{i,t}$	Vector of country-specific variables of bank i at time t
c	Credit risk
$\mathbf{D}$	DTW distance matrix
DEP_ASSET	Ratio of customer deposits to total assets
DER_ASSET	Ratio of derivatives to total assets
$\mathbf{D}_{\text{Metric}}$	DTW distance matrix given an underlying metric
$\mathbf{D}_{\text{SE}}$	DTW distance matrix based on the squared Euclidean metric
d	DTW distance
d_{bound}	Threshold value of the DTW distance
d_{uu}	Pairwise DTW distance
d_{uv}	Pairwise DTW distance
$\hat{d}_{uv}$	Standardized pairwise DTW distance modeled with RBFs
$d_{uv;\text{Metric}}$	Pairwise DTW distance given an underlying metric
d_{vu}	Pairwise DTW distance
E	Superscript denoting the model specification for ECB announcements
$\mathbf{E}$	Identity matrix in the context of RBFs
$\mathrm{E}(\cdot)$	Expected value function
$\mathrm{E}\left[\exp\left(\mathrm{i}tX\right)\right]$	Characteristic function of the SDI for random variable X
$\mathrm{E}(R_{i,t} \mid \Omega_t^r)$	Expected return of firm i at time t given Ω_t^r (generic notation)
$\mathrm{E}(\Delta S_{i,t} \mid \Omega_t^s)$	Expected CDS spread change of firm i at time t given Ω_t^s (generic notation)
e	Event
$\exp(\cdot)$	Exponential function
F	Superscript denoting the model specification for Fed announcements
FG, FG, FG_t	Forward guidance factor of ECB's monetary policy (at time t)
F^j	Matrix of latent factors extracted via PCA
FULL_AFF_l	Dummy variable equal to 1 for U.S. banks subject to full liquidity requirements, and 0 otherwise
GIIPS	Dummy variable equal to 1 for EU banks located in Greece, Italy, Ireland, Portugal, or Spain, and 0 otherwise
G_SIB	Dummy variable equal to 1 for global systemically important banks, and 0 otherwise

H	Hypothesis (numbered; defined by risk type—market (m), credit (c), or liquidity (l); distinguished by region (*U.S.* or *EU*); may include sub-hypotheses labeled A and B; if applicable, specified separately for stocks (*stock*) and CDSs (*CDS*))
$\mathbf{I}$	Identity matrix
i	Imaginary unit in the context of the SDI
i	Generic observation or cross-sectional unit index
j	Superscript indicating ECB press release or press conference window (not applicable to the Fed, which has only a single window)
k	Index for RBFs
k_{lf}	Number of PCA-derived latent factors
$\mathcal{L}$	Lagrange function
LCR_PROXY	LCR proxy (ratio of liquid assets to demand deposits and short-term funding)
$Level_t$	Level of the risk-free interest rate at time t
LIFE, LIFE_i	Dummy variable equal to 1 for life insurers, and 0 otherwise
LOAN_ASSET	Ratio of total loans to total assets
l	Liquidity risk
$\ln(\cdot)$	Natural logarithm function
$MAR_{i,t}$	Market-adjusted return of bank i at time t
MOD_AFF_l	Dummy variable equal to 1 for U.S. banks subject to less stringent liquidity requirements, and 0 otherwise
m	Market risk, market (in the context of returns of an index)
N	Number of observations (sample length)
NSFR_PROXY	NSFR proxy (ratio of the sum of total equity, long-term funding and customer deposits to total assets)
N_t	Number of nonmissing returns in the cross-section of N firms (banks, insurers) in the respective portfolio at time t
n_{hf}	Number of times series of high-frequency changes in interest rates
PROV_LOAN	Ratio of loan loss provisions to total loans
p	P-value
path_conf, $path\_conf_t$	Aggregate of the three ECB's press conference window factors (at time t)
path, *path*, $path_t$	Path factor of Fed's monetary policy (at time t)
p_{ed}	Inflection point of the empirical distribution to determine d_{bound}
p_{rb}	Desired residual effect at the next center in the context of RBFs
QE, *QE*, QE_t	Quantitative easing factor of ECB's monetary policy (at time t)

Q_i	Number of nonmissing returns in the time series of firm i (banks, insurers)
$\mathbb{R}$	Set of real numbers
R^2	Coefficient of determination
$R_{i,t}$	Return of firm i (banks, insurers) at time t
$\overline{R}_m$	Average market index return in the estimation window
$R_{m,t}$	Market index return at time t
$\mathbb{R}^n$	n-dimensional real vector space
$\mathbb{R}^{N \times N}$	Set of all real-valued $N \times N$ matrices
ROA	Return on assets
R_{rb}	Distance between to different centers of RBFs
$\mathbb{R}^+$	Set of strictly positive real numbers
r	Superscript denoting the model specification based on stock returns
$\overline{r}$	Average of pairwise cross-sectional correlations of the regression residuals in the estimation period
$\text{rank}(\cdot)$	Rank function
$\langle r_{cc} \rangle$	Average CC return
r_{rb}	Distance in the context of RBFs
S	Satellite
$S(\cdot)$	Standard deviation function
$SAR_{i,t}$	Standardized abnormal return of firm i (banks, insurers) at time t
$SDI(\alpha, \beta, \gamma, \delta)$	Stable distribution function
SEC_ASSET	Marketable security investments to total assets
SIZE	Size (natural logarithm of total assets)
$Slope_t$	Slope of the risk-free interest rate at time t
SOV_DEBT	Dummy variable equal to 1 for the sovereign debt crisis (2010-05-02–2013-06-30), and 0 otherwise
$SR_{i,t}$	Standardization factor of firm i (banks, insurers) at time t
$S(SAR_t)$	Cross-sectional standard deviation of standardized abnormal returns at time t
$S(U)$	Standard deviation of standardized ranks
s	Superscript denoting the model specification based on CDS spread changes
s_{cc}	Standard deviation of CC returns
si	Superscript denoting the model specification based on CDS spread changes (single-index model)
$\text{sign}(\cdot)$	Signum function

T	Number of days in the estimation window
TIER1_RAT	Tier 1 ratio
TIER1_RAT^2	Squared Tier 1 ratio
T_p	Number of monetary policy events
T_s	Number of days in the event window
t	Independent variable of the characteristic function (Fourier transform) in the context of the SDI
t	Time index
(t_1, t_2)	Event window from t_1 to t_2, without implying specific relative days like t_{+1} or t_{+2}
$\tan(\cdot)$	Tangent function
target^E, $target^E$, $target_t^E$	Target factor of ECB's monetary policy (at time t)
target^F, $target^F$, $target_t^F$	Target factor of Fed's monetary policy (at time t)
timing, $timing$, $timing_t$	Timing factor of ECB's monetary policy (at time t)
$U_{i,t}$	Standardized rank of firm i (banks, insurers) at time t
u	Index of a CC
$\mathrm{Var}(\cdot)$	Variance function
$\mathrm{Var}[CPE_i(t_1, t_2)]$	Variance of the cumulative prediction error of firm i (banks, insurers) in the event window (t_1, t_2)
$\boldsymbol{V}_i$	Covariance matrix of the prediction error of firm i (banks, insurers)
v	Index of a CC
$\mathbf{v}$	Vector in the context of RBFs
W	Sum of RBFs
w	Index for RBFs
X	Random variable
$\boldsymbol{X}_i$	Matrix of estimation period values to compute $\boldsymbol{V}_i$
$\boldsymbol{X}_i^*$	Matrix of event period values to compute $\boldsymbol{V}_i$
$X_{i,t}$	Standardized abnormal return of firm i (banks, insurers) at time t, additionally adjusted using cross-sectional variance
X^j	Matrix containing time series of high-frequency interest rate changes around ECB and Fed announcements
x	Risk category (market, credit, and liquidity)
$\mathbf{x}$	Point of a RBF
$\mathbf{x}_i$	Sample point i of a RBF
$\mathbf{x}_w$	Center of a RBF
y_i	Sample value in the context of RBFs
$\hat{y}_i$	Modeled value in the context of RBFs

$y(\mathbf{x})$	One-dimensional function in the context of RBFs
Z	Z statistic of the parametric test
Z_c	Z statistic of the nonparametric test

Other Symbols

∞	Infinity
$\in$	Element of
$\langle\cdot\rangle$	Function returning the sample average
$>$	Greater than
$\geq$	Greater than or equal to
$<$	Less than
$\leq$	Less than or equal to
$\neq$	Not equal to
$\sqrt{\cdot}$	Square root function
$\times$	Multiplication operator
$(\cdot)'$	Transpose operator (vector or matrix)
$(\cdot)^{-1}$	Inverse operator for a matrix
$\lvert\cdot\rvert$	Absolute value operator
$\lVert\cdot\rVert$	Norm operator for vectors or matrices
€	Euro
$	United States dollar
%	Percent

1 Introduction

1.1 General Remarks

The past two decades have brought seismic shifts to the banking landscape. The global financial crisis (GFC) of 2008, the emergence of Bitcoin later that year, and the global wave of interest rate hikes beginning in 2022 have each marked pivotal turning points in the evolution of the modern banking system. These events reflect profound transformations in how banking risks are managed and regulated, how institutions operate in different interest rate environments, and how technological dynamics influence capital allocation.

The 2007 United States (U.S.) subprime mortgage crisis escalated into the GFC, culminating in the collapse of Lehman Brothers on September 15, 2008. In its aftermath, significant Basel reforms were introduced. The crisis spread rapidly across interconnected financial markets, with Europe particularly affected due to high exposure to U.S. subprime assets. Governments responded with large-scale interventions, exposing taxpayers to substantial risks (Basel Committee on Banking Supervision, 2011). Despite these measures, the severity of the shock triggered a global recession.

One key cause was identified as inadequate financial regulation. In response, the Basel Committee on Banking Supervision (BCBS) launched a major overhaul aimed at strengthening financial system resilience and minimizing future reliance on public funds (Basel Committee on Banking Supervision, 2011). To this end, the BCBS enhanced the regulation of market, credit, and liquidity risks through Basel II.5, Basel III, and Basel IV, with liquidity risk addressed globally for the first time.[1] These reforms entail substantial changes to proprietary trading, lending practices, the term structure of funding, and asset allocation, prompting important questions about their implications for banks.

In parallel, the cryptocurrency (CC) market—sparked by the publication of the Bitcoin whitepaper by Nakamoto (2008) on October 31, 2008—evolved from a niche innovation into a volatile but increasingly institutionalized asset class (Baur et al., 2018). This development raised new questions about risk, diversification, regulatory oversight, and the potential disintermediation of traditional financial intermediaries. While CCs influence banks in various ways, this dissertation explicitly refrains from evaluating whether banks should invest in them. Instead, it focuses on the practical question of how such an investment could be structured, assuming a bank decides to include CCs in its asset allocation—whether for proprietary trading or for client asset management services. Given the heavy-tailed and highly volatile nature of CC returns (Majoros and Zempléni, 2018; Börner et al., 2025), the assumptions of traditional portfolio theory—as introduced by Markowitz (1952)—are not suitable for structuring such investments.

[1] Officially, Basel IV is designated as the finalization of the Basel III reforms. However, it is commonly referred to as Basel IV by bank representatives. To better distinguish the Basel Accords, this dissertation employs the term Basel IV.

More than a decade later, surging inflation, driven among other factors by the COVID-19 pandemic and Russia's war of aggression against Ukraine, prompted central banks such as the Federal Reserve (Fed) and the European Central Bank (ECB) to initiate a rapid and synchronized cycle of interest rate hikes, marking a decisive end to the prolonged era of ultra-loose monetary policy. Given the interest rate sensitivity of deposit and lending activities, it is essential to understand how interest rate changes affect bank profitability. In addition, it is conceivable that a shifting interest rate environment may influence banks' investment behavior. It is therefore reasonable to assume that bank risk may also be affected. Moreover, the potential spillover effects of interest rate changes by the Fed on capital markets in the Eurozone—and, conversely, of ECB policy on U.S. markets—warrant closer examination.

These developments underscore the increasing complexity and interdependence of modern banking systems. Regulation has a direct impact on bank profitability and risk exposure; monetary policy influences not only macroeconomic conditions but also reshapes the risk–return profiles of financial intermediaries; and financial innovation continues to challenge conventional asset allocation strategies and established risk management models in the banking sector. As regulatory frameworks tighten, monetary conditions shift, and technological advancements—such as CCs—gain momentum, banks must continuously adapt to a landscape of evolving constraints and opportunities.

Against this backdrop, this dissertation empirically investigates these dynamics by analyzing how capital markets respond to the Basel reforms and to monetary policy announcements by the Fed and the ECB. In addition, it examines how an investment in CCs could be structured from a portfolio perspective. In doing so, it contributes to a deeper understanding of how institutional, policy-driven, and technological forces jointly influence banks and financial market outcomes in an increasingly complex environment.

To clearly and systematically pursue the analytical objectives, the dissertation is structured into five sections that guide the reader through the core areas of investigation. After outlining three transformative developments in banking, Sec. 1 provides a concise overview of the evolution of the Basel regulatory frameworks, recent inflation dynamics, and the foundational principles of CCs. Building on this, the research gaps that motivate the analyses in the following sections are identified. Subsequently, the research approaches are introduced, beginning with an overview of the event study methodology relevant to the first two analyses. This is followed by a description of the segmentation process developed for the CC market in the third analytical part. The introductory section concludes by highlighting the contributions of the three analyses.

Building upon this foundation, Sec. 2 presents a comprehensive investigation into how regulatory reforms—namely Basel II.5, Basel III, and Basel IV—have reshaped market, credit, and liquidity risks, and how these regulatory-driven risk adjustments have influenced the expected profitability and perceived risk of shareholders and creditors of U.S. and European Union (EU) banks. Furthermore, the analysis identifies which bank- and country-specific characteristics explain the heterogeneous responses of investors.

Given the methodological parallels, the subsequent Sec. 3 examines the impact of interest rate hikes by the Fed and the ECB on shareholders and creditors of banks and insurance companies from the U.S. and the Eurozone. Insurers are included in the analysis due to the interest rate sensitivity of their business models, which is particularly pronounced in the case of life insurers.

Section 4 explores how the CC market can be segmented based on statistical characteristics. The underlying method is deliberately formulated in a generic way to ensure broad applicability across various user groups. In this dissertation, however, the method is discussed in the context of the banking sector, where it serves as a basis for examining investment decisions in CCs within proprietary trading and client asset management.

Finally, Sec. 5 synthesizes the findings of the three analyses, discusses their broader implications, and highlights potential directions for future research.

1.2 Fundamentals and Research Gap

1.2.1 Basel Banking Regulation - Postcrisis Reforms

Building on the initial overview of Basel II.5, Basel III, and Basel IV, this section outlines the institutional and regulatory foundations of post-crisis banking regulation and derives the key research gap motivating the first empirical analysis. The BCBS was established in 1974 in response to the collapse of the German Herstatt Bank and is hosted by the Bank for International Settlements (BIS) in Basel. It comprises representatives from national central banks and banking supervisory authorities; as of July 8, 2025, 28 jurisdictions are members of the BCBS (Basel Committee on Banking Supervision, 2025).[2] It designs supervisory standards for international banking regulation which, however, do not have binding legal force and require transposition into supranational or national law.

The first regulatory framework was adopted in 1988 with the introduction of Basel I, marking the first internationally coordinated effort to address credit risk in a uniform manner (Basel Committee on Banking Supervision, 1988). This framework was later expanded to include market risk through the 1996 Amendment to Basel I, which represented the first attempt to regulate market risk on a global scale (Basel Committee on Banking Supervision, 1996). Introduced in 2004, Basel II expanded upon Basel I by establishing a more risk-sensitive framework based on three pillars: minimum capital requirements, supervisory review, and market discipline (Basel Committee on Banking Supervision, 2004). It also allowed banks to use internal models for risk assessment, subject to regulatory approval.

The gradual implementation of Basel II coincided with the onset of the U.S. subprime crisis in 2007, which escalated into the GFC and ultimately led to the bankruptcy of Lehman Brothers in 2008.

[2]For instance, the EU is a member of the BCBS, represented through both the ECB and the Single Supervisory Mechanism (SSM), which operates under the auspices of the ECB.

In addition to the U.S., Europe was particularly affected due to the close interconnection of capital markets and high levels of exposure to U.S. subprime assets. The public sector had to intervene with massive liquidity injections, capital aid, and guarantees, putting taxpayers at considerable risk (Basel Committee on Banking Supervision, 2011). In the U.S., measures included the Emergency Economic Stabilization Act of 2008 and the American Recovery and Reinvestment Act of 2009, while in the EU, one example is the European Economic Recovery Plan of 2008. Despite these efforts, the financial and real economy suffered greatly, leading to the Great Recession. A key cause was weak financial regulation, prompting the Basel Committee to overhaul the framework to bolster global financial resilience and reduce reliance on public funds (Basel Committee on Banking Supervision, 2011).

To this end, the BCBS tightened regulation of market, credit, and liquidity risks through Basel II.5, Basel III, and Basel IV, introducing global liquidity standards for the first time. Although these accords contain broader reforms addressing other aspects of the financial system, the first empirical analysis, presented in Sec. 2, specifically focuses on the regulation of these three financial risks. The reforms have significant implications for trading, lending, term structure, asset selection, and funding, prompting questions about how effectively they influence banks' risk-taking behavior and how they may, in turn, affect financial performance. Beyond these effects, it remains crucial to evaluate whether the regulatory changes—consistent with the objectives of the BCBS—help reduce systemic risk and moral hazard, and ultimately minimize the need for taxpayer-funded bailouts. With the regulatory framework now fully implemented, its aggregate effect can be assessed. While the BCBS conducted impact assessments and scenario analyses ex ante, it appears more appropriate to direct the question of the reforms' actual effects to the market itself rather than to the institutions involved or those with a vested interest (Schäfer et al., 2016). Examining market reactions provides assumption-free insights, as markets incorporate new information with at least semi-strong information efficiency (Fama, 1970). Since regulation affects both risk and profitability, an event study represents an adequate and robust empirical approach, and thus serves as the empirical foundation of the first analysis in Sec. 2.

Despite the Basel reforms' relevance, little research evaluates their post-crisis market impact. Only two studies, by Bruno et al. (2018) and Simion et al. (2024), analyze market responses to Basel liquidity regulation in Europe. The first finds a weak negative stock reaction, especially when isolating liquidity measures from simultaneously announced capital regulations, but does not consider later reforms such as the adoption of the net stable funding ratio (NSFR). The second examines creditor reactions and suggests an increase in default risk. However, both studies omit the U.S., which further justifies renewed analysis.

This paper extends prior research by focusing on market and credit risk regulation, enabling a targeted assessment of key changes in proprietary trading and banks' core function: lending. The analysis covers both bank stocks and credit default swaps (CDSs), capturing the perspectives of shareholders and creditors alike. This dual approach allows an evaluation of whether the regulatory goal of risk reduction was achieved. The sample focuses on U.S. and EU banks—two jurisdictions heavily affected by the financial crisis, representing the world's most important capital markets, and offering long CDS time series—making them particularly suitable for assessing regulatory impact. By restricting the European sample to EU banks, the analysis maintains a consistent regulatory context while allowing comparison with the U.S., where implementation practices differ. Although the BCBS sets standards for "internationally active banks", this term lacks a precise definition and leaves room for national discretion (Basel Committee on Banking Supervision, 2012). As a result, key elements such as liquidity rules and capital requirements apply only to the largest U.S. banks, leading to substantial cross-jurisdictional differences. In addition, the question arises whether variations in the strictness of national implementation may undermine a level playing field.

Against this backdrop, the analysis in Sec. 2 addresses three key research gaps in the post-crisis Basel regulatory framework. First, by examining shareholder and creditor reactions, it sheds light on how the regulation of market, credit, and liquidity risks influences banks' profitability and perceived risk. Second, it assesses whether the reforms have effectively mitigated bank risk and curtailed moral hazard—thus supporting the overarching goal of preventing future taxpayer-funded bailouts. This question extends beyond academic interest, carrying significant societal and political implications. The public backlash to crisis-era interventions, as exemplified by the Occupy movement, underscores its broader relevance. Third, a cross-jurisdictional comparison between the U.S. and the EU enables an assessment of whether divergent implementation practices undermine regulatory consistency and distort competitive conditions, thereby challenging the global level playing field envisaged by the BCBS.

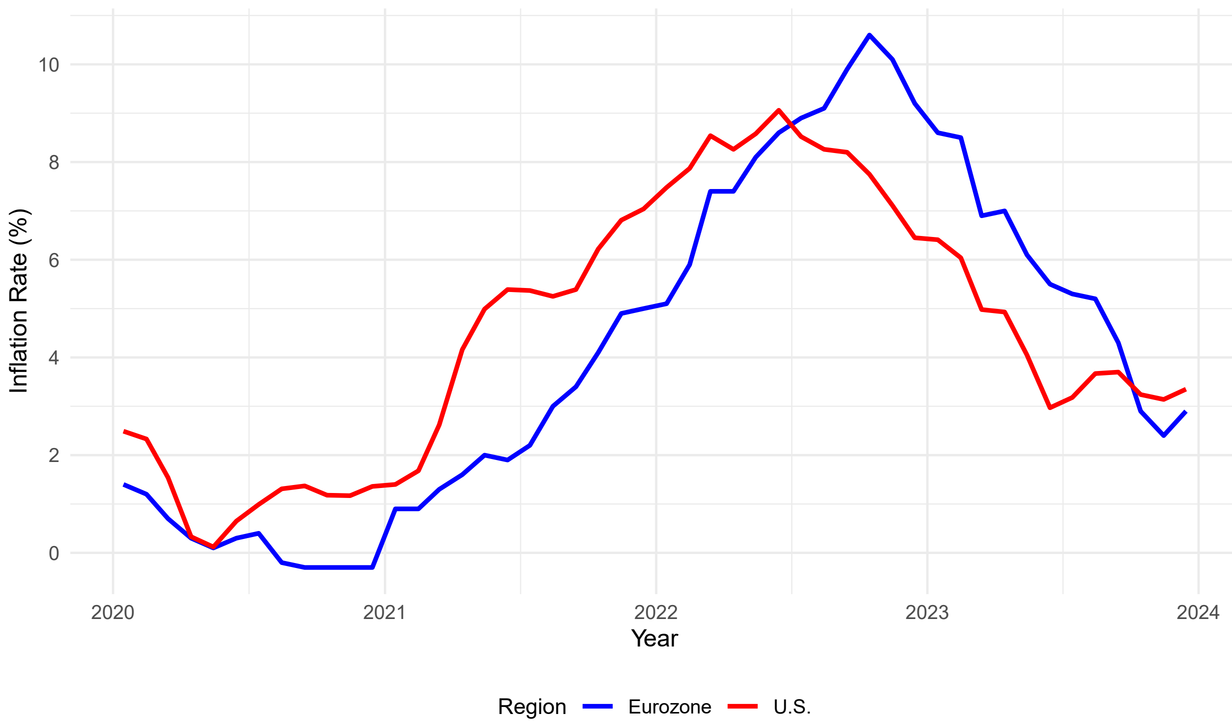
1.2.2 Interest Rate Hikes

In addition to regulatory reforms, recent institutional shifts—notably the interest rate hikes implemented by central banks since 2022—have profoundly affected financial markets and, by extension, banks and insurers. These entities are particularly exposed due to their central role in financial intermediation through deposit-taking, lending, and risk transformation. As both the Basel reforms and recent monetary policy shifts are institutional in nature, and as both are analyzed using a consistent event study framework, this dissertation first turns to monetary policy effects in Sec. 3, before exploring the impact of technological innovation through CCs in Sec. 4.

The COVID-19 pandemic triggered a period of substantial economic disruption, marked by strained global supply chains and followed by large-scale fiscal support programs implemented by governments in response to the crisis. Examples in the U.S. include the Coronavirus Aid, Relief, and Economic Security Act of 2020, the Consolidated Appropriations Act of 2021, and the American Rescue Plan Act of 2021. In addition to national-level interventions, the EU launched the NextGenerationEU recovery instrument and the temporary Support to mitigate Unemployment

Risks in an Emergency program, both introduced in 2020. These developments contributed to the emergence of inflationary pressures that intensified in early 2022 following Russia's invasion of Ukraine. The war introduced a new wave of geopolitical uncertainty, which—alongside the economic sanctions imposed on Russia, particularly by the U.S. and Europe—contributed to surging energy and commodity prices, exacerbating existing supply-side constraints. As a result, inflation reached historic highs: in the U.S., it peaked at 9.1% in June 2022, while in the Eurozone it rose to 10.6% in October 2022, as displayed in Fig. 1.

Figure 1: Eurozone and U.S. Inflation Rates



The continued escalation of inflation ultimately necessitated a fundamental shift in monetary policy, marking a clear departure from the previously expansionary stance. The Fed initiated a series of interest rate hikes, raising the federal funds rate to its highest level in decades. The ECB followed on July 21, 2022, implementing its first rate increase after years of historically low and, at times, negative interest rates. These policy measures were aimed at containing inflation and restoring price stability.

In light of this fundamental macroeconomic shift, it is essential to examine how financial intermediaries are affected, given the particular role that banks and insurance companies play in the transmission of monetary policy, making them primary targets of such interventions (Yin et al., 2010; Yin and Yang, 2013; Ricci, 2015). This is rooted in their inherent function as financial intermediaries, primarily through deposit-taking and lending activities as well as risk transformation. Consequently, the analysis extends beyond banks to also include insurers.

The relationship between monetary policy and financial markets represents a core area of financial research, with a broad body of literature indicating that increases in interest rates generally lead to declines in stock valuations (Thorbecke, 1997; Angeloni and Ehrmann, 2003; Rigobon and Sack, 2004; Bernanke and Kuttner, 2005). Broadly, the literature can be divided into studies that assess the impact of monetary policy on general stock indices—such as the S&P 500 or STOXX50E—and those that investigate sector-specific responses, particularly in the banking (Aharony et al., 1986; Akella and Greenbaum, 1992; Fiordelisi et al., 2014; Ricci, 2015; English et al., 2018; Bats et al., 2023) and insurance sectors (Brewer et al., 2007; Czaja et al., 2009; Jensen et al., 2019; Killins and Chen, 2022).

Although there is extensive literature on how monetary policy affects financial markets, important research gaps persist. First, the majority of existing studies focus on interest rate cuts, even though previous research has shown that the effects of rate increases are not symmetric to those of rate reductions (Yin and Yang, 2013; Ricci, 2015). While rate cuts are typically intended to stimulate the economy, rate hikes tighten financial conditions, raise capital costs, and can lead to liquidity constraints. Therefore, the implications of rate hikes cannot simply be inferred from the existing findings on rate cuts. This asymmetry highlights the need to analyze the recent tightening cycle on its own empirical terms.

Second, empirical research on rate hikes remains limited, especially in light of the significant policy shifts observed since 2022. The few studies that explicitly analyze interest rate increases (e.g. Aharony et al. (1986); Akella and Greenbaum (1992); Ricci (2015); English et al. (2018)) are based on data from earlier tightening cycles and do not reflect the current macro-financial environment. Consequently, there is a need for new empirical evidence capturing the market reactions to the recent, historically large interest rate hikes by the ECB and the Fed.

Third, most studies examine monetary policy effects within single economic regions—typically the U.S. or the Eurozone—and neglect the strong interdependence between these highly integrated markets. Although some research has investigated spillover effects from Fed policy into European markets (Conover et al., 1999; Ammer et al., 2010; Hausman and Wongswan, 2011), these analyses mainly focus on non-financial sectors. The impact of ECB policy on U.S. markets has received even less attention, with only Groba and Serrano (2020) analyzing its influence on U.S. corporate default risk. This shortcoming is explicitly highlighted by Altavilla et al. (2019). Given the interconnectedness of global financial markets and the role of banks and insurers as transmitters of monetary policy, examining cross-border effects in these sectors is particularly important.

Finally, the literature has primarily focused on stock markets, thereby reflecting only changes in profitability. However, stock price reactions alone do not capture the full spectrum of market perceptions, particularly from a creditor's perspective. CDS spreads offer a complementary measure by reflecting changes in perceived credit risk. While Koch and Islam (2024) analyze the effects of federal funds rate hikes on U.S. bank risk, their study excludes insurers, omits international spillover effects, and relies on alternative risk proxies rather than CDS spreads.

The study in Sec. 3 addresses these gaps by jointly analyzing stock and CDS market reactions to interest rate hikes. By covering both banks and insurers in the U.S. and the Eurozone, it provides a comprehensive and differentiated analysis of the impact of monetary policy on profitability and perceived risk, while also offering new insights into bilateral cross-border spillover effects between two of the world's most integrated financial systems.

1.2.3 Cryptocurrencies

In the following, the evolution and core characteristics of CCs are explored, beginning with the launch of Bitcoin in 2008, which marked the advent of decentralized digital assets. Since then, the CC market has grown significantly and, as of July 1, 2025, comprises approximately 18.29 million CCs, including both coins and tokens, with a total market capitalization of $3.33 trillion (CoinMarketCap, 2025).[3] To provide a foundation for the research gap addressed in Sec. 4, the key properties of CCs are briefly introduced.

Initially designed as a decentralized peer-to-peer electronic payment system, Bitcoin and later altcoins have evolved into a distinct and increasingly recognized asset class (Baur et al., 2018).[4] At the heart of CCs lies the innovation of distributed ledger technology (DLT), which is commonly implemented through a blockchain structure (Bariviera et al., 2017). Unlike traditional government-backed currencies, which rely on a central authority—usually a bank—to process and verify transactions, blockchain-based CCs facilitate peer-to-peer transfers by eliminating the need for such intermediaries.

In the monetary theory literature, there is a broad consensus that an asset must fulfill the following three characteristics to be classified as money: medium of exchange, store of value, and unit of account (Cheah and Fry, 2015; Dwyer, 2015). The first function is questionable, as user behavior suggests that the vast majority of CC holders are inactive and do not use them for payments (Glaser et al., 2014). The store of value and unit of account functions are undermined by the high volatility of CC returns and their pronounced tail risks (Polasik et al., 2015; Balcilar et al., 2017; Osterrieder et al., 2017; Gkillas et al., 2018; Börner et al., 2025). Therefore, CCs are regarded as a young and inherently speculative asset class, whose price is determined solely by supply and demand (Cheah and Fry, 2015; Yermack, 2024). The classification of CCs as a distinct asset class can further be justified by their high internal correlation and their low correlation with currencies, as well as with gold, bonds, or stocks (Osterrieder et al., 2017; Baur et al., 2018; Corbet et al., 2018b; Schmitz and Hoffmann, 2020; Yermack, 2024).

[3]Coins are CCs that operate on their own native blockchain (e.g., Bitcoin or Ethereum), while tokens are digital assets created via smart contracts on existing blockchains. Tokens depend on the host network's infrastructure and may represent various functions, rights, or assets.

[4]Altcoins refer to all CCs that were developed after Bitcoin.

Given their unique return characteristics and the growing interest from institutional investors, an important consideration is their potential to enhance portfolio diversification and function as a safe haven asset (Bouri et al., 2017).[5] This potential must be assessed independently from the inherent risks associated with this asset class, such as hacking attacks on CC exchanges and the absence of government or central bank backing, which could otherwise provide regulatory protection, especially for small, uninformed and uncoordinated investors. Furthermore, CCs are prone to speculative bubbles, a tendency attributed to their lack of fundamental intrinsic value (Cheah and Fry, 2015; Corbet et al., 2018a). While hedging these risks is undoubtedly challenging (Corbet et al., 2018b), it lies beyond the scope of the research question explored in Sec. 4.

Building on these fundamentals, a central consideration is how this new and speculative asset class can be accessed and utilized from the perspective of investors, and thus by banks. As noted in the introduction, CCs affect various aspects of the financial system, including, for example, the potential for disintermediation. However, the analysis in Sec. 4 focuses specifically on the perspective of CC investors. The following discussion does not aim to evaluate whether banks or their clients should invest in CCs. Rather, it explores how such investments might be implemented in practice, assuming that the decision to engage with this asset class has already been made. It is also conceivable that demand for CC investment options will rise on the client side. In this context, particular attention is given to the roles banks may take—either through proprietary trading or by offering crypto-related investment products within their asset management services. Given the elevated risk profile of CCs and the strict capital requirements for proprietary trading, banks are likely to allocate only a small portion of their overall portfolio to such assets.

Despite the growing relevance of CCs in institutional portfolio strategies, a key gap remains in the development of a robust, data-driven segmentation framework for the CC market, tailored to the needs of professional investors and portfolio managers. While existing approaches—such as the CC market index CRyptocurrency IndeX (CRIX) proposed by Trimborn and Härdle (2018) or the CC index CCi30 by Rivin et al. (2017)—aim to represent the market through top-down constructions based on market capitalization or trading volume, they primarily focus on large, established CCs and are susceptible to survivorship bias. These methods fail to reflect statistical properties among assets and overlook the distributional characteristics critical for portfolio construction and risk management.

Traditional portfolio theory, particularly the optimization framework proposed by Markowitz (1952), assumes normally distributed returns. However, CC returns are heavy-tailed and exhibit significant deviations from normality, rendering classical mean-variance approaches inadequate in this context (Majoros and Zempléni, 2018; Börner et al., 2025). As a result, there is a disconnect

[5] A safe haven asset is an investment that maintains or increases its value during periods of market stress, typically exhibiting low or negative correlation with riskier assets.

between the statistical realities of CCs and the models used to manage them.

In professional portfolio management, a core–satellite approach segments the investment universe into a core of statistically homogeneous assets and a satellite of more heterogeneous positions. The core market is replicated using suitable asset selections that minimize tracking error, while the satellite, representing a small share of the overall portfolio, targets specific market segments with the aim of generating above average returns or enhancing diversification through low correlation with the core assets (Amenc et al., 2012). Although core–satellite strategies are well established in traditional asset management (e.g. sector selection of corporate bonds), there has been little academic attention on their application to the CC asset class, particularly in terms of data-driven identification of a "core" consisting of statistically similar CCs. A structured segmentation of the market into a core (stable, statistically homogeneous assets) and a satellite (more volatile, less predictable assets) has the potential to reduce monitoring costs and improve risk control—especially in light of operational risks and the fast-paced dynamics of the CC market (Trimborn et al., 2020). Monitoring costs are lower because the core can be represented by a smaller number of statistically similar assets, which reduces the need for constant oversight and individual risk assessment across a wide range of positions.

Accordingly, this dissertation addresses the lack of a robust segmentation methodology that accounts for the distributional properties of CC returns and supports practical portfolio construction. Section 4 aims to close this gap by applying modern pattern recognition techniques to identify statistically coherent groupings within the CC market, based on empirical risk–return characteristics, thereby facilitating more efficient investment decisions.

1.3 Research Approach

1.3.1 Event Study Methodology

Building on the previously identified research gaps, the following section outlines the research approaches, beginning with the fundamental framework of the event study. This methodology forms the foundation of the first two investigations in Sec. 2 and Sec. 3, which therefore serves as the starting point.

The event study methodology, which dates back to Ball and Brown (1968); Fama et al. (1969), is fundamentally suited to testing the null hypothesis that markets process information efficiently, as well as to examining whether specific events have an impact on security prices (Binder, 1998). This dissertation adopts the latter perspective, applying the methodology to examine how regulatory announcements and monetary policy decisions affect capital markets and what economic insights can be drawn.

The starting point of an event study is the assumption of at least the semi-strong form of informational efficiency in capital markets, which ensures that new, price-relevant information is immediately reflected in market prices. The efficient market hypothesis (EMH) as proposed by

Fama (1970) distinguishes between three levels of informational efficiency. In the weak form, all historical information is reflected in prices; in the semi-strong form, all publicly available information is additionally incorporated; and in the strong form, even insider information is fully reflected in market prices. In practice, it is generally assumed that markets exhibit at least semi-strong form of informational efficiency, which provides a sufficient basis for the application of the event study methodology. This ensures that regulatory changes introduced by the BCBS, as well as interest rate decisions by the Fed and the ECB, are incorporated into asset prices at the time of their announcement, allowing their effects to be empirically assessed.

Since Ball and Brown (1968); Fama et al. (1969), stock returns have been used to examine the impact of events on profitability from the perspective of shareholders. In more recent years, increasing attention has also been paid to how events affect the risk of the firms under investigation (Bessembinder et al., 2009; Horváth and Huizinga, 2015; Moenninghoff et al., 2015; Schäfer et al., 2016; Pancotto et al., 2020). This trend is partly due to the growing availability of CDS data. To analyze the effects on firm-level risk, the perspective of creditors can be captured using bonds or CDSs. As a first step, the functioning of a CDS contract is explained in order to subsequently derive why CDSs are more suitable than bonds for analyzing creditor risk. CDSs can be interpreted as over-the-counter (OTC) default insurance for debt, in which a compensation payment is made following the occurrence of a predefined credit event. In such contracts, the protection buyer pays a periodic premium to the protection seller, and receives a compensation payment in the event of default of the reference obligation (e.g., a bond or loan) prior to the contract's maturity (Houweling and Vorst, 2005). Importantly, compensation is paid regardless of whether the protection buyer actually incurs a loss from the default, which is why these derivatives are used not only for hedging purposes but also for speculation. The periodic premium—known as the CDS spread—is quoted in basis points (bps) (1% = 100 bps) and applied to the notional amount, serving as a market-based measure of credit risk. These contracts allow for the trading of counterparty risk and are often standardized through guidelines issued by the International Swaps and Derivatives Association (ISDA). Based on the preceding explanation of CDS mechanics, it is demonstrated why CDSs are more appropriate than bonds for analyzing creditor risk in the context of an event study.

A key challenge in using bonds lies in the fact that corporate bonds differ in terms of maturity, credit rating, and liquidity. Consequently, it is unclear how to aggregate the various price changes in order to measure the effect of the event (Andres et al., 2021). In contrast, CDS contracts are available with different maturities, with a five-year horizon being the de facto standard, thus ensuring better comparability across firms (Bessembinder et al., 2009). Moreover, CDSs are generally more liquid than bonds, implying that they reflect changes in credit risk more accurately and in a more timely manner (Ericsson et al., 2009). In addition, the use of CDSs requires tracking only a single instrument per firm, rather than analyzing a set of bonds with varying liquidity profiles and trading intensities (Bessembinder et al., 2009). Finally, CDS spreads capture pure credit risk, whereas bond prices are influenced by additional risk components (Longstaff et al., 2005). An example is interest rate risk. Based on this rationale, CDS spreads—rather than bonds—are employed in the event studies conducted in Sec. 2 and Sec. 3 to examine the impact on creditor risk.

With increasing data granularity, the likelihood of detecting information-induced abnormal effects rises. Consequently, daily data are favored over weekly or monthly observations to more accurately capture short-term market reactions (Morse, 1984). From a temporal perspective, a distinction is made between the estimation window and the event window. The estimation window is used ex ante to econometrically estimate the parameters that are then applied within the event window to determine the expected returns and the expected CDS spread changes. To avoid the confounding influence of the examined event on the model parameters, the event window and the estimation window are generally kept separate (MacKinlay, 1997).[6] As described in the methodology sections of Sec. 2 and Sec. 3, there is an inherent trade-off in determining the appropriate length of the estimation window. While a longer window increases the accuracy of parameter estimation, it also increases the risk of confounding influences on the estimates, as well as the risk that the process generating stock returns or CDS spread changes may have shifted (Strong, 1992).

Even more critical are confounding events within the event window, as they directly impact the calculation of the abnormal effect and compromise the causal attribution of the observed market reaction to the event under investigation. Short event windows with daily data help reduce the likelihood of confounding events, increase the power of statistical tests, and thereby lower the probability of a type II error (Schäfer et al., 2016). Therefore, short event windows of a maximum of three trading days are utilized in both analyses. Additionally, considerable effort is undertaken to identify potential confounding events (see Sec. 2.5.5 and Sec. 3.6).

Furthermore, it is essential to ensure a certain degree of liquidity in the stocks and CDSs under investigation. Otherwise, in the case of an insignificant reaction of the analyzed portfolio, it would remain unclear whether this is due to the irrelevance of the event or rather to the absence of trading activity. Therefore, separate liquidity criteria are defined for stocks and CDSs in both empirical investigations.

The mechanism for calculating abnormal returns and CDS spread changes within the event window is identical.[7] The abnormal return $\epsilon^{*r}_{i,t}$ for firm i at time t is calculated as the difference between the actual return $R_{i,t}$ and the expected return $\mathrm{E}(R_{i,t}|\Omega^r_t)$

$$\epsilon^{*r}_{i,t} = R_{i,t} - \mathrm{E}(R_{i,t}|\Omega^r_t), \tag{1}$$

[6]The abnormal effect of an event can also be analyzed using dummy variables without a temporal separation between the estimation and event windows (Binder, 1985a,b). However, this approach is not pursued in this dissertation.

[7]Returns and CDS spread changes are calculated as logarithmic differences of stock prices and CDS spreads, respectively, since continuous changes are conceptually more likely to approximate a normal distribution.

whereby Ω_t^r is the conditioning information for the normal return model. Analogously, the expected CDS spread changes $\mathrm{E}(\Delta S_{i,t}|\Omega_t^s)$ are subtracted from the actual CDS spread changes $\Delta S_{i,t}$ to obtain the abnormal CDS spread changes $\epsilon_{i,t}^{*s}$

$$\epsilon_{i,t}^{*s} = \Delta S_{i,t} - \mathrm{E}(\Delta S_{i,t}|\Omega_t^s). \tag{2}$$

The conditioning information for the normal CDS spread model is denoted by Ω_t^s.[8] Subsequently, methods for estimating expected returns and CDS spread changes, $\mathrm{E}(R_{i,t}|\Omega_t^r)$ and $\mathrm{E}(\Delta S_{i,t}|\Omega_t^s)$ are discussed. The procedures are explained only for returns, as they were originally developed for stocks. However, they can be analogously applied to debt instruments and, consequently, to CDS spreads (MacKinlay, 1997).

Referring to the price development of a stock as "abnormal" presupposes the existence of a return-generating process, which serves as a benchmark from which the performance of the stock can deviate in the first place (Brown and Warner, 1985). In the calculation of abnormal returns, a fundamental distinction can be made between economic and statistical models. The former, in addition to statistical assumptions, incorporate assumptions about investor behavior (MacKinlay, 1997). Examples of economic models include the capital asset pricing model (CAPM) by Sharpe (1964); Lintner (1965); Mossin (1966) and the arbitrage pricing theory (APT) by Ross (1976). While the CAPM posits that the expected return of an asset depends on its covariance with the market portfolio, the APT assumes that the expected return results from a linear combination of multiple risk factors (MacKinlay, 1997). Further elaboration on economic models is omitted, as this dissertation relies exclusively on statistical models. This decision is based on the fact that the validity of economic assumptions is questionable in practice, and results may be sensitive to violations of these assumptions (Campbell et al., 1997).

The most common statistical models are mean-adjusted, market-adjusted, and market models (Brown and Warner, 1985). In the first approach, the arithmetic mean of the return is calculated within the estimation window for stock i and used as a proxy for the expected return in the event window. Hence, Ω_t^r is a constant. In the market-adjusted model, the abnormal return is directly calculated during the event period by taking the difference between the return of stock i and the return of a market index on each day. Thus, the market return is used as the expected return and Ω_t^r is the market return. The market model of Sharpe (1963) postulates a linear relationship between the return of stock i and that of a market index. The parameters are estimated within the estimation window using ordinary least squares (OLS), and subsequently applied to calculate expected returns

[8] In the introduction, the generic notations $\epsilon_{i,t}^{*r}$ and $\epsilon_{i,t}^{*s}$ are employed to denote abnormal returns and CDS spread changes, respectively, as this section solely outlines the fundamental mechanics of their computation. Throughout the dissertation, superscripts r and s denote model specifications based on stock returns and CDS spread changes, respectively, with si used in the latter case to explicitly indicate the CDS single-index model specification. This notation is consistently applied to parameters, error terms, and related expressions.

in the event window. Again, Ω_t^r corresponds to the market return.

To estimate expected and, consequently, abnormal returns, the analyses in Sec. 2 and Sec. 3 employ the market model proposed by Sharpe (1963). Additionally, the former analysis also calculates market-adjusted returns, for which no estimation window is required. This additional calculation in Sec. 2 serves to account for potential distortions in the beta factor, as the study period covers the time of the GFC and the European sovereign debt crisis. Expected and thus abnormal CDS spread changes are estimated using a comparable market model, proposed by Andres et al. (2021). This is a multifactor model based on a CDS market index, augmented with additional regressors, as prior research has shown that macroeconomic factors have significant explanatory power for CDS spreads (Collin-Dufresne et al., 2001; Ericsson et al., 2009). As with market-adjusted returns, market-adjusted CDS spread changes are also calculated in Sec. 2 for the same reasons.

To avoid model-specific terminology at this stage, this introductory section refers to abnormal returns and CDS spread changes in general, irrespective of the estimation approach applied. Within the event window, cumulative abnormal returns and CDS spread changes are first calculated for each firm i, followed by the computation of their average across all N portfolio firms.[9] This enables overall inferences regarding the event of interest (Campbell et al., 1997).

In a first step, the test statistics used in Sec. 3 to assess average cumulative abnormal returns and CDS spread changes per event are discussed. To determine whether these values differ significantly from zero, both parametric and nonparametric procedures are available. The key distinction lies in the underlying assumptions: parametric tests require the abnormal effects to be normally distributed, whereas nonparametric tests make no such distributional assumptions. The selection of an appropriate testing method is a complex task, as various factors can significantly affect the validity of the results.

An initial consideration is event clustering, as the interest rate hikes affect all portfolio firms simultaneously. This induces cross-sectional correlation of abnormal returns and CDS spread changes, which can bias test statistics and lead to overrejection of the null hypothesis (Kolari and Pynnönen, 2010). Separately, an event-induced increase in volatility relative to the estimation period can have the same effect if not properly addressed (Brown and Warner, 1985). To account for the latter issue, the standardized cross-sectional test proposed by Boehmer et al. (1991) is employed as the parametric test. This approach is further refined to also account for cross-sectional correlation caused by event clustering, as proposed by Kolari and Pynnönen (2010).

[9] Specific abbreviations such as cumulative abnormal return (CAR), cumulative abnormal CDS spread change ΔCAS, cumulative market-adjusted return (CMAR), and cumulative market-adjusted CDS spread change $\Delta CMAS$ are intentionally avoided at this point, as each implies a distinct estimation method. These abbreviations are introduced only in the respective sections, once the underlying models—namely the market model and the market-adjusted model—have been formally defined.

Although an approximately normal distribution can be assumed given a sufficiently large estimation window, the nonparametric rank test proposed by Corrado and Zivney (1992) is additionally applied, as it shares the robustness and power properties of the adjusted test by Boehmer et al. (1991)—a point highlighted by Kolari and Pynnönen (2010). Furthermore, Andres et al. (2021) provide evidence that the rank test is particularly well-suited for analyzing CDS data.

As part of the analysis of the BCBS financial risk regulation in Sec. 2, aggregated stock and CDS market reactions are calculated separately for each type of risk—market, credit, and liquidity—and for each portfolio, based on multiple individual events within each risk category. Following the aggregation of average cumulative abnormal returns and CDS spread changes across these events, the question arises once again as to which testing procedure is appropriate. However, since the number of events is limited to a maximum of 26 (in the case of credit risk events), conventional parametric or nonparametric tests cannot be readily applied. Therefore, a block bootstrap procedure is employed, which originates from the event study methodology proposed by Armstrong et al. (2010). At its core, this method constructs a distribution under the null hypothesis that the regulation in question did not occur.

Building on a univariate assessment of the significance of stock and CDS market reactions, the question arises—both from capital market and regulatory perspectives—as to what determines market reactions in the cross-section. From the standpoint of regulators and central banks, such insights are crucial for assessing the effectiveness and precision of policy measures, identifying potential unintended consequences, and monitoring systemic vulnerabilities. To this end, cumulative abnormal returns and CDS spread changes for each firm i are regressed on relevant explanatory variables, using either OLS or alternative estimation techniques such as random effects models. These regressions typically incorporate firm-specific, country-level, and macroeconomic variables.

1.3.2 Segmentation of the Cryptocurrency Market

To address the identified research gap—a lack of a quantitative, distribution-sensitive segmentation tailored to the CC universe—a novel methodological procedure is introduced in Sec. 4. The goal is to systematically group CCs based on their empirical distributional characteristics, allowing for a more nuanced understanding of structural relationships within the market. This is particularly relevant from the perspective of investing banks, both in the context of proprietary trading and in asset allocation on behalf of their clients, as it enables more informed and structured investment decisions in the CC market.

The returns of CCs are notably heavy-tailed and deviate substantially from the assumptions of normality (Osterrieder et al., 2017; Gkillas and Katsiampa, 2018; Gkillas et al., 2018). These empirical characteristics stand in stark contrast to the foundations of traditional portfolio theory, particularly the optimization framework proposed by Markowitz (1952), which relies on normally distributed returns. Consequently, classical mean-variance approaches prove inadequate in capturing the true risk–return dynamics of CCs, revealing a fundamental disconnect between the statistical nature of these assets and the models traditionally used to allocate them.

To account for the distinctive risk–return profile of CCs, Sec. 4 introduces a novel methodology that explicitly captures both tail risk and the evolving dynamics of the CC market. As a first step, the defining characteristics of the sampled CCs are identified, providing the basis for segmenting the CC universe into a statistically homogeneous core and a heterogeneous satellite segment. The analysis begins with the mean and standard deviation of CC returns, following the approach of Markowitz (1952). In addition, Majoros and Zempléni (2018); Kakinaka and Umeno (2020); Börner et al. (2025) demonstrate that the stable distribution (SDI) provides a suitable framework for modeling CC returns, particularly in the tail area. To explicitly account for tail risk, the tail parameter α of the SDI is incorporated into the analysis. This serves as a distinguishing criterion between CCs with strongly pronounced tails and those with less pronounced tails. These three variables constitute the foundation for the subsequent analysis intended to segment the CC universe.

The dynamic time warping (DTW) algorithm enables the identification of similar patterns in the temporal evolution of the three statistical parameters. Originally developed by Sakoe and Chiba (1978) for speech recognition, it has over time proven to be relevant for clustering and classification tasks (Giorgino, 2009). More specifically, the DTW algorithm serves as the foundation of the structure-discovering, bottom-up approach to CC segmentation developed in Sec. 4.

In the context of proximity measures, a fundamental distinction is made between distance measures and similarity measures. As the name implies, DTW distances fall into the category of distance-based measures. Without delving too deeply into the computational details (see Sec. 4.4), the DTW distance is calculated for each pair of CCs; the smaller the DTW distance between two CCs, the more statistically similar the CCs are, and vice versa. This inverse relationship between distance and similarity is a defining property of distance-based measures such as DTW. The pairwise DTW distances calculated in this manner must be organized such that CCs with the smallest DTW distances (i.e., highest statistical similarity) are grouped together in order to perform the segmentation. The challenge and objective of the segmentation process lie in identifying a specific DTW distance—purely from the data—that represents the boundary between a statistically homogeneous core and a heterogeneous periphery of CCs. This method is briefly outlined below.

Before the DTW distance is computed, a (local) distance matrix must first be calculated for each pair of CCs. To enhance robustness, the Manhattan, Euclidean, and squared Euclidean distances are all computed. This means that for each CC pair, three distance matrices—each based on one of the respective metrics—serve as the input for the DTW algorithm. Subsequently, the DTW algorithm computes the DTW distance $d_{uv;\text{Metric}}$ for each pair $u, v = 1, \dots, N$ of the N CCs and each metric, where the value range is $[0; +\infty)$. Based on the three (local) distance matrices per CC pair, the DTW algorithm finds the optimal alignment by warping the time axis of one series to match the other (Sakoe and Chiba, 1978).

After computing the three $d_{uv;\text{Metric}}$ for all CC pairs, three matrices $\mathbf{D}_{\text{Metric}} \in \mathbb{R}^{N \times N}$ for the N CCs are constructed, each corresponding to one of the metrics, with elements $d_{uv;\text{Metric}}$. These square matrices are symmetric, satisfying $d_{vu} = d_{uv}$, with zeros on the diagonal $d_{uu} = 0$, and strictly positive values in all off-diagonal positions. Within $\mathbf{D}_{\text{Metric}}$, the homogeneous CCs of the core are to be separated from the heterogeneous CCs in the satellites, which is equivalent to the problem of finding structures in $\mathbf{D}_{\text{Metric}}$. For this purpose, methods commonly used in the analysis of hierarchical matrices are fundamentally suitable, as they assist in detecting patterns (Liu et al., 2012; Hackbusch, 2015).

First, $\mathbf{D}_{\text{Metric}}$ is sorted according to the maximum row or column sums. Then, the individual elements $d_{uv;\text{Metric}}$ of the distance matrix are normalized between 0 and 1, and the height profile of the sorted distance matrix is modeled using radial basis functions (RBFs) (a detailed explanation can be found in I). This smoothing is necessary because the height profile of the $d_{uv;\text{Metric}}$ prevents an accurate determination of the cut-off point and thus the identification of the symmetric core. A threshold d_{bound} is derived by identifying the inflection point in the empirical distribution function of the normalized elements in the upper-triangular part of the DTW distance matrix, capturing the p_{ed} percent smallest values and thereby separating a statistically homogeneous core from the heterogeneous periphery.

To enhance robustness, the procedure is carried out using the three $\mathbf{D}_{\text{Metric}}$, and a CC is assigned to the core only if it belongs to the core according to all three metrics. Otherwise, the CC is classified as part of the heterogeneous satellite segment.

1.4 Contribution

After outlining the methodological foundations of the three papers, this section discusses their scientific contributions. As the title of this dissertation suggests, these contributions lie in the analysis of key challenges to the banking system and their implications for banks, their shareholders and creditors, as well as for regulators, central banks, and other policymakers—ultimately affecting taxpayers. Specifically, the dissertation focuses on three major developments in the post-GFC banking environment: (1) the regulatory reforms addressing market, credit, and liquidity risk under Basel II.5, Basel III, and Basel IV; (2) the interest rate hikes by the Fed and the ECB in response to post-pandemic inflation, which was further intensified by geopolitical tensions following Russia's war of aggression against Ukraine; and (3) the evolution of CCs as an asset class since Bitcoin's inception in 2008. The remainder of this section details the contributions of each paper, beginning with the single-author publication presented in Sec. 2.

Published in 2025 in *The Quarterly Review of Economics and Finance* (Vol. 101, Article 101990, doi: 10.1016/j.qref.2025.101990), this paper makes three principal contributions to the literature on post-GFC banking regulation and capital market responses. First, it provides a comprehensive empirical evaluation of the market effects of the Basel II.5, Basel III, and Basel IV accords. Unlike the BCBS's scenario-based analyses to estimate the potential impact of these reforms, this study adopts an independent, market-based approach using event study methodology to capture actual market reactions. By examining both stock and CDS markets, the paper simultaneously reflects the perspectives of shareholders and creditors, offering a dual lens through which to assess changes in profitability and perceived risk. Building on previous studies such as Bruno et al. (2018) and Simion et al. (2024), which have provided important insights into the effects of liquidity regulation in Europe, this paper complements the existing literature by broadening the scope of analysis to include regulatory events related to market, credit, and liquidity risk, and by examining both EU and U.S. banks. Additionally, the cross-sectional analysis demonstrates that heterogeneity in market reactions can be attributed to differences in bank-specific characteristics and country-level factors. This enables a comprehensive assessment of how BCBS regulation has affected bank profitability and risk across market, credit, and liquidity dimensions in both the EU and the U.S.

Second, the paper highlights cross-jurisdictional implementation differences and their capital market implications. While EU banks exhibit significant negative stock market reactions to both market and credit risk regulation, U.S. banks respond more moderately or not at all. This divergence is primarily attributed to the stricter and more comprehensive implementation of Basel standards in the EU, whereas the U.S. regulatory framework was already shaped by the earlier adoption of the Dodd-Frank Act in 2010, with the Volcker Rule as a prominent component restricting proprietary trading. In addition, significant regulatory exemptions—such as those for small bank holding companies (SBHCs)—have limited the scope of Basel implementation in the U.S., contributing to the more muted market responses observed. Similarly, CDS spreads of EU banks rise significantly in response to credit risk regulation, reflecting heightened creditor risk due to reduced bailout expectations. In contrast, the CDS response in the U.S. is weaker and insignificant, likely due to the earlier adoption of the Dodd-Frank Act, which had already lowered bailout expectations (Schäfer et al., 2016). The findings question whether a level regulatory playing field truly exists and support concerns voiced in the literature about implementation asymmetries and regulatory arbitrage (Wagster, 1996).

Third, the results are interpreted in the context of regulatory theory. The observed market reactions—particularly the negative response from EU shareholders and the rise in CDS spreads—suggest that the Basel reforms have succeeded in shifting risk away from taxpayers and back onto shareholders. This outcome is consistent with the public interest theory of regulation by Needham (1983), which views the regulator as a social planner seeking to maximize overall welfare by minimizing the public burden of financial crises. At the same time, the study finds no evidence supporting the capture theory proposed by Stigler (1971), which posits that regulatory outcomes are shaped by lobbying and industry influence. Despite documented cases of lobbying and weakened reform proposals, the lack of positive stock market reactions indicates that the reforms were not perceived as favoring the banking sector. Instead, the empirical findings align with the BCBS's post-crisis objectives of strengthening financial resilience, reducing moral hazard, and protecting public funds (Basel Committee on Banking Supervision, 2011).

Taken together, these contributions offer a multidimensional perspective on the real-world effects of banking regulation and underscore the importance of consistent enforcement across jurisdictions. The paper enriches the academic debate by providing robust empirical evidence, cross-country comparisons, and an assessment of regulatory effectiveness—insights that are highly relevant to scholars, regulators, and policymakers alike.

Building on this, the second analysis of the dissertation, presented in Sec. 3, employs a methodologically similar event study and is currently under review at *The European Journal of Finance*.[10] This paper empirically examines how interest rate hikes by the Fed and ECB affect banks and insurers, focusing on both shareholders and creditors in the U.S. and the Eurozone. The additional inclusion of insurers is justified by their role—alongside banks—as primary targets of monetary policy interventions, stemming from their risk transformation function (Yin et al., 2010; Yin and Yang, 2013; Ricci, 2015).

The study makes three central contributions to the literature on monetary policy transmission and its effects on banks and insurers. First, the paper contributes to a relatively underexplored area of research by focusing on the effects of interest rate hikes, rather than cuts, on financial institutions. Additionally, prior research shows that rate cuts and hikes have asymmetric effects: while cuts stimulate the economy, hikes tighten financing conditions and increase capital costs, making findings from rate cuts not directly transferable to rate hikes (Yin and Yang, 2013; Ricci, 2015). Hence, recent contractionary cycles—particularly those since 2022—have received limited attention. Earlier studies on rate hikes (e.g. Aharony et al. (1986); Akella and Greenbaum (1992); Ricci (2015); English et al. (2018)) are outdated and do not reflect the current post-pandemic and geopolitical context. By focusing on the 2022–2023 tightening cycle, this study captures the unique dynamics of a monetary policy regime shift after a long period of historically low interest rates.

Second, the paper expands the analytical scope by incorporating both stocks and CDS spreads, thereby capturing effects on both profitability and perceived credit risk. While prior research has largely focused on stock markets alone, this dual-perspective approach allows for a more nuanced understanding of monetary policy transmission channels, because stock prices reflect changes in expected returns for shareholders, while CDS spreads capture changes in perceived default risk from the perspective of creditors. This is particularly relevant for financial institutions, whose business models are highly sensitive to interest rates and liquidity conditions. This study builds on the methodology of Gürkaynak et al. (2005) and Altavilla et al. (2019) to construct monetary policy shocks, allowing for a precise identification of unexpected policy changes and their transmission effects. Beyond the purely univariate analysis of abnormal returns and CDS spread changes, the

[10] Status as of July 8, 2025.

cross-sectional analysis explores how and to what extent the abnormal responses can be attributed to the shock components.

Third, the paper addresses a major gap in the literature regarding cross-border monetary policy spillovers between the U.S. and the Eurozone. Most existing research concentrates on domestic effects, often neglecting the strong interdependence of integrated financial markets. While earlier works (Conover et al., 1999; Ammer et al., 2010; Hausman and Wongswan, 2011) have examined spillovers from Fed policy, they focus on non-financial sectors and largely ignore the banking and insurance industries. In contrast, spillover effects of ECB policy on U.S. markets have received little attention, with only Groba and Serrano (2020) examining the impact on the default risk of U.S. firms. A key contribution of this paper is therefore the analysis of spillover effects from ECB policy into U.S. markets.

The results show that unexpected interest rate hikes typically lower stock prices and raise CDS spreads domestically—indicating declining profitability and rising credit risk. At the same time, cross-border effects are significant but asymmetric for European stocks, with positive reactions to Fed tightening, likely due to relative attractiveness effects and capital flows from the U.S. to the Eurozone. Creditors of Eurozone institutions react with increasing CDS spreads as well, which can be explained by the fact that the CDS portfolios include exclusively large cross-border institutions. With regard to ECB policy, U.S. shareholders exhibit statistically significant yet directionally ambiguous reactions, whereas creditors respond with increased risk perception, reflected in rising CDS spreads. The ambiguous stock market response in the U.S. to ECB measures may be explained by the country's market-oriented financial system, which includes a higher share of small, publicly listed financial intermediaries with limited cross-border activity—especially within the bank portfolio.

Overall, the study provides robust evidence that monetary policy shocks by the Fed and the ECB have measurable effects on both shareholder value and credit risk, and that these effects are transmitted internationally in complex and institution-specific ways. By integrating stock and credit market responses across two major jurisdictions, and by employing well-established shock identification frameworks, this paper offers valuable insights for central banks and financial market participants navigating the implications of tightening cycles in an increasingly interconnected global economy.

The final analysis in Sec. 4 investigates how the growing CC market can be segmented from a banking perspective—based on statistical characteristics—into a homogeneous core and heterogeneous satellites, in order to inform investment decisions. The scientific relevance, the robustness of the empirical analysis, and the novelty of the findings are underscored by the publication of the article in 2022 in the *Journal of Asset Management* (Vol. 23, pp. 310–321, doi: 10.1057/s41260-022-00267-z). This paper makes three principal contributions to the literature on CC portfolio construction and financial market segmentation.

First, a novel, data-driven methodology is introduced to distinguish between a statistically homogeneous core and a heterogeneous satellite segment within the CC market. In contrast to existing index-based approaches relying on market capitalization and liquidity thresholds—such as the CRIX by Trimborn and Härdle (2018) or the CCi30 by Rivin et al. (2017)—the proposed method segments the market based on statistical properties of return, volatility, and tail risk. This enhances the existing body of research on risk-aware asset classification.

Second, the use of DTW introduces a flexible, time-series-based approach to financial market analysis. Originally developed by Sakoe and Chiba (1978) for speech recognition, DTW has since found widespread application across various scientific fields, e.g., electrocardiogram analysis and clustering of gene expression profiles (Giorgino, 2009). Its application to asset-level financial data represents a methodological innovation, capable of capturing temporal variation in statistical characteristics beyond static correlation measures.

Third, the findings have practical relevance for institutional asset management of banks. The segmentation approach enables a core–satellite portfolio construction strategy, allowing the core market to be tracked with a reduced number of representative CCs, while satellite CCs can be used selectively to improve diversification and risk-adjusted returns. This is particularly important in light of the high volatility, operational risk, and market fragmentation within the CC universe (Trimborn et al., 2020). Finally, the methodology is generalizable beyond CCs. The segmentation framework provides a transferable tool for identifying structurally similar and dissimilar assets in other asset classes, supporting improved risk management and strategic asset allocation.

Collectively, the three papers address key challenges facing the banking sector in the aftermath of the GFC—spanning regulatory reform, monetary policy, and the rise of digital assets. While the first two papers offer capital market-based evidence on how regulation and interest rate hikes affect financial institutions, the third paper contributes a novel methodological approach to CC portfolio construction. Together, these studies provide a multidimensional perspective on regulatory effectiveness, monetary transmission, and digital asset segmentation, offering insights that support more informed decision-making by banks, their shareholders and creditors, regulators, central banks, and other policymakers, with broader societal implications—including for taxpayers.

2 Market Reactions to the Basel Reforms: Implications for Shareholders, Creditors, and Taxpayers

2.1 Abstract

This paper evaluates the impact of postcrisis financial risk regulation introduced through Basel II.5, Basel III, and Basel IV on EU and U.S. bank shareholders and creditors. Specifically, an event study is used to analyze 15 market events, 26 credit events, and 13 liquidity events. This approach allows for an assessment of the impact on profitability and risk, providing a basis for deriving the effectiveness of these regulations in reducing risks for the public sector and taxpayers. Significant negative stock market reactions by EU banks in response to market and credit risk regulations are observed. In contrast, U.S. banks exhibit no clear significant stock market reactions, largely due to the Dodd-Frank Act and especially more lenient regulatory implementation. EU creditors responded to credit risk regulation with significantly rising CDS spreads, signaling higher risks due to diminished bailout expectations. The cross-sectional analysis highlights the importance of bank- and country-specific factors in explaining heterogeneous reactions. The results suggest that the Basel reforms have successfully shifted risks from taxpayers back to shareholders and reduced moral hazard among creditors. However, the significant differences between the EU and U.S. market reactions raise concerns about the establishment of a level playing field, underscoring the need for more consistent implementation across jurisdictions.

2.2 Introduction

Significant Basel reforms were introduced in response to the 2007 U.S. subprime crisis, which escalated into a GFC and the Lehman Brothers bankruptcy in 2008. The crisis spread rapidly through interconnected global financial markets, with Europe being especially affected due to high levels of exposure to U.S. subprime assets. The public sector was forced to intervene with unprecedented injections of liquidity, capital assistance, and guarantees, which placed taxpayers at significant risk of substantial losses (Basel Committee on Banking Supervision, 2011). Examples include the Emergency Economic Stabilization Act of 2008 and the American Recovery and Reinvestment Act of 2009 in the U.S., while in the EU, the European Economic Recovery Plan was adopted in 2008. Despite various interventions, the consequences for both the financial system and the real economy were so severe that a global recession, the so-called Great Recession, followed. A key cause of the crisis was identified as insufficient regulation of the financial system, to which the BCBS responded with a comprehensive revision. The objective was to increase the resilience of the global financial system, prevent future crises, and avoid further reliance on taxpayer funds (Basel Committee on Banking Supervision, 2011).

To achieve these objectives, the BCBS significantly strengthened the regulation of financial risks—namely, market, credit, and liquidity risk—through the Basel II.5, Basel III, and Basel IV accords, whereby the liquidity risk was addressed globally for the first time. This enforcement involves far-reaching changes to proprietary trading, lending, the term structure, funding, and asset selection, raising questions about the implications for banks. As the regulatory framework for all three types of risk has been fully announced, it is now possible to quantify the overall effect, which is crucial for understanding the actual impact of the regulation. Although the BCBS conducted various scenario analyses and impact studies to assess the hypothetical impact, it is useful to examine market reactions. This approach allows an investigation independent of any assumptions because markets price new information with at least semistrong information efficiency (Fama, 1970). Because regulatory initiatives have a prospective impact on a bank's profitability as well as its risk, the effects can be captured by an event study, which is the empirical foundation of this paper.

Despite the significance of the Basel reforms, there is surprisingly limited literature assessing the effectiveness of these policy responses post-GFC. To the author's knowledge, only two papers address market reactions to Basel's financial risk regulation. The impact of liquidity regulation on banks is analyzed for European samples by Bruno et al. (2018) and Simion et al. (2024). The first paper focuses on stocks and reveals that shareholders reacted negatively. However, when liquidity announcements made alongside other Basel III measures are excluded, the effect is only weakly significant. The second paper examines the impact on creditors, and the authors suggest that default risk has increased. Although liquidity announcements have already been examined for Europe, the U.S. market is missing in both analyses. Furthermore, the first paper includes only events up to January 2013, while the second liquidity ratio, the NSFR, was subsequently published. Therefore, liquidity regulation is also included in the analysis.

This paper complements previous studies by analyzing the important aspects of market and credit risk regulation, which allows for a thorough examination of the significant changes in proprietary trading and the core activity of banks, namely, lending. The analysis involves both EU and U.S. bank stocks and CDSs, which has the advantage of examining the position of both bank owners and creditors. Therefore, whether the intended effect of risk reduction succeeds can be investigated. The sample selection is based on the fact that both U.S. and EU banks were particularly affected by the crisis, making it plausible to study the regulatory impact in these jurisdictions. In addition to the importance of both financial markets, sufficiently long time series of CDSs are available. Focusing on EU banks rather than all European banks ensures a consistent regulatory environment. This focus allows for an analysis of whether differences in reactions between EU and U.S. banks arise from varying implementation practices. The BCBS mandates and monitors the application of its rules for "internationally active banks". However, this term is not precisely defined, giving national authorities some discretion (Basel Committee on Banking Supervision, 2012). This lack of precision has led to significant differences in implementation between the EU and U.S., as, for example, liquidity rules and certain capital requirements are applied only to the largest U.S. banks.

This paper makes contributions in three key areas. First, the analysis of stock and CDS market reactions enables an assessment of how the extensive post-GFC regulation of the three financial risks impacts banks' profitability and risk. Additionally, it demonstrates that bank-specific and country-specific factors account for heterogeneous responses. Second, the inclusion of both EU and U.S. banks allows for an examination of differences due to divergent regulatory implementations across jurisdictions. Third, from a policy perspective, it allows for an evaluation of the BCBS's effectiveness in achieving its objectives of reducing risk for the public sector and taxpayers. The empirical design and results are briefly presented. Using event study methodology, the overall effects of EU and U.S. stock and CDS market reactions to carefully selected 15 market events, 26 credit events and 13 liquidity events by the BCBS and their significance are computed for both equally weighted and market-weighted portfolios. Next, a cross-sectional analysis is conducted to identify bank- and country-specific drivers of the potentially heterogeneous market reactions, as it cannot be assumed that all banks reacted similarly to the regulation.

Regarding aggregated market responses, market risk regulation leads to a distinct negative and significant EU stock market reaction from -11.82% for the equally weighted portfolio up to -20.16% for the market-weighted response, implying a wealth loss for shareholders. In contrast, U.S. bank stocks show no significant reaction. These differences can be attributed to the stricter EU implementation as well as to the fact that small regional U.S. banks are part of the sample that generally do not engage in proprietary trading. A further explanation is the unchanged risk–return profile of U.S. banks under the Basel regulation, largely due to the existing Volcker Rule, which restricts trading for U.S. institutions. Neither U.S. nor EU bank creditors react at all. Significant differences also exist in terms of credit risk regulation. A clearly negative and significant EU stock market reaction is observed, with aggregated responses of -20.08% for the equally weighted reaction up to -40.91% for the market-weighted reaction. Although the U.S. reaction is negative as well, with market-weighted reactions up to -27.41%, significance cannot be clearly proven here. The reason is that, in the EU, the credit risk framework applies uniformly to all banks, whereas in the U.S., SBHCs are exempt, and only larger institutions face specific requirements. U.S. and EU creditors perceive higher risks and react with rising CDS spreads, with only the EU reaction being significant. The equally weighted portfolio achieves a value of 35.19%, while the market-weighted response is stronger with 40.33%. Increased EU CDS spreads suggest that creditors are bearing greater risk because of the reduced likelihood of bailouts induced by regulation. An explanation for the insignificance of U.S. creditors is provided by Schäfer et al. (2016), who show rising CDS spreads following the introduction of the Dodd-Frank Act, attributing it to a reduction in bailout probability. This observation implies that the Basel credit risk framework has no additional impact. Liquidity regulation has no impact on EU and U.S. shareholders and EU creditors, whereas the U.S. CDS reaction cannot be analyzed due to confounding events.[11] The lack of a U.S. reaction may be attributed to the fact that U.S. liquidity rules apply exclusively to large banks, as well as the stronger

[11] This limitation also applies to the cross-sectional analysis of U.S. CDS spreads.

liquidity position of these institutions during and after the GFC (European Banking Authority, 2012; Dietrich et al., 2014). While Bruno et al. (2018) report a significant negative shareholder reaction, this paper finds no effect. However, the aggregated market reaction is comparable in magnitude. This finding suggests that the six additional events examined in this paper may be considered noise events with limited capital market significance, indicating that the relevance of events diminishes over time. While CDS spreads increased similarly as in the study by Simion et al. (2024), no significance was found here, likely due to methodological differences and a reduced sample size. Additionally, the authors include Swiss and Norwegian banks that are not part of the EU. Finally, significance in their analysis is only observed in the (0;0) window, with similar results for the (-1;+1) window, which is also utilized in this paper.

In addition to aggregated market reactions, cross-sectional analysis demonstrates the importance of bank- and country-specific characteristics for individual reactions. Concerning market risk regulation, a bank's capitalization lowers CDS spreads in both the U.S. and the EU. Furthermore, increased market risk and classification as a global systemically important bank (G-SIB) lead to higher CDS spreads in the U.S. In contrast, G-SIBs reduce U.S. returns, whereas elevated market risk and a bank' being located in Greece, Italy, Ireland, Portugal or Spain (GIIPS) result in reduced returns for EU shareholders. Regarding credit risk, there is a positive but decreasing effect of a bank's capitalization on U.S. stock market reactions, while risk costs negatively affect returns. Additionally, banks subject to regulation show lower returns than SBHCs do. U.S. creditors respond to risk costs with higher CDS spreads. In the EU, the feedback loop between sovereign and bank credit risk in GIIPS banks positively influences shareholders and reduces CDS spreads. Bank capitalization and risk costs also exert a negative effect. With regard to liquidity risk, more liquid balance sheets and higher charter values reduce EU CDS spreads, suggesting greater resilience to liquidity shocks. Conversely, the feedback loop raises creditor risk by worsening funding conditions. In the EU stock market, the feedback loop reduces returns, which also holds for reduced funding mismatches. In the U.S. stock market, large banks subject to full liquidity requirements experience decreasing returns, reflecting a one-sided penalty and competitive disadvantage. The results remain robust across various tests, including the application of different models for estimating abnormal returns and CDS spread changes, the use of alternative benchmark indices, and a thorough analysis of potential confounding events.

In addition to the purely economic assessment from the perspective of shareholders and creditors, the results can be framed within the context of the BCBS's objectives. To evaluate whether regulation serves the public interest, two strands of literature can be identified, whereby a market reaction can be expected in both cases but with different signs. The public interest theory developed by Needham (1983) postulates that the regulator acts in the public interest as a social planner who maximizes overall welfare—in this case, at the expense of the banks. This role is particularly relevant against the backdrop of the GFC, during which governments used taxpayers' money to bail out banks. The

BCBS has emphasized the importance of preventing such a scenario. Of course, a banking system in which banks adequately perform their transformational functions serves the public interest (Bruno et al., 2018). The capture theory developed by Stigler (1971) argues the opposite. Here, regulated industries influence the regulator by lobbying to gain privileges. Indeed, such tendencies can also be observed in the regulatory process of the banking industry with the occasional significant weakening of regulatory proposals (see Tab. A.21, Tab. A.22, Tab. A.23).

Regardless of the risk type, there is no significant positive stock market reaction that supports the capture theory of Stigler (1971), neither in the EU nor in the U.S. Although the banking industry's lobbying has weakened regulatory proposals, the absence of a positive stock market reaction, coupled with the overall tightening of regulation, aligns with the public interest theory proposed by Needham (1983). During the GFC, bank risks were transferred to the public sector. The negative stock market reactions suggest a reversal of this process, with a welfare transfer from bank shareholders back to taxpayers through the reallocation of risk. This mechanism appears to be more pronounced in the EU, likely due to the stricter initial implementation of the regulations. In contrast, the U.S. reactions may also have been tempered by the earlier introduction of the Dodd-Frank Act in 2010, as well as the fact that the U.S. stock sample includes many small regional banks, which are generally less affected by the related regulations. The CDS market reactions show that the success of regulation in achieving risk reduction remains uncertain. This uncertainty arises from the absence of significant and decreasing CDS spreads. This finding does not inherently imply that the intended risk reduction has been unsuccessful, nor does it suggest that regulation inadvertently amplifies a bank's default risk. From a creditor's perspective, regulation generates two opposing dynamics. On the one hand, there is the sought-after risk reduction leading to lower CDS spreads. On the other hand, reduced expectations of creditor bailouts increase CDS spreads (Sarin and Summers, 2016; Schäfer et al., 2016; Pancotto et al., 2020). In this context, the latter factor takes precedence in the eyes of creditors, which is reinforced by the fact that the CDS portfolios exclusively encompass major banks.

Given these findings, it can be concluded that the objectives of the BCBS have been largely achieved through the revision of financial risk regulation. The risks borne by taxpayers during the GFC were transferred back to shareholders, while the regulation also contributed to mitigating moral hazard among bank creditors by reducing bailout expectations. However, the significant differences in actual implementation, as evidenced by the divergent responses in the U.S. and the EU, raise doubts about whether a truly level regulatory playing field has been established. A key policy implication is the need to enforce more consistent implementation across BCBS member states.

This paper contributes to the broad literature on the market evaluation of bank regulation, which has a long tradition in the U.S. and is driven largely by deregulatory measures (Dann and James, 1982; James, 1983; Allen and Wilhelm, 1988; Cornett and Tehranian, 1989; Slovin et al., 1990;

Cornett and Tehranian, 1990; Brook et al., 1998; Carow and Heron, 1998; Bhargava and Fraser, 1998; Mamun et al., 2004; Yildirim et al., 2006). In addition to the papers mentioned by Bruno et al. (2018) and Simion et al. (2024), the closest connection in terms of content is with the papers that examine the impact of Basel I on stocks (Eyssell and Arshadi, 1990; Cooper et al., 1991; Lu et al., 1999; Wagster, 1996). The bottom line is that shareholders in various countries react negatively, there are redistribution effects favoring smaller banks, and Basel I is unable to establish a level playing field. The present paper also relates to more recent literature that analyzes regulatory changes post-GFC, with an increasing use of CDSs due to the growing availability of CDS data (Horváth and Huizinga, 2015; Moenninghoff et al., 2015; Schäfer et al., 2016; Pancotto et al., 2020).

The paper is structured as follows: Section 2.3 outlines the key changes introduced by Basel II.5, Basel III, and Basel IV regarding the regulatory treatment of market, credit, and liquidity risks. It also describes the event selection and evaluation process and presents the actual implementation in the U.S. and EU. Section 2.4 discusses hypotheses related to both aggregated and heterogeneous market reactions. Section 2.5 details the data, event study design, block bootstrap significance test, cross-sectional analysis, and approach to handling confounding events. Section 2.6 presents the results and discussion. Section 2.7 addresses additional robustness checks and limitations. Section 2.8 concludes the paper.

2.3 Regulatory Background and Event Dates

2.3.1 Regulation of Financial Risks from Basel II.5 to Basel IV

The regulation of the three financial risks changed considerably in the wake of the 2007 GFC. Basel II.5 can be understood as the BCBS's immediate crisis response, addressing banks' market risk and, to an extent, their trading books' capitalization, risk management and disclosure requirements. The market risk framework that was valid until the GFC in 2007 was the 1996 Amendment that was intended to supplement Basel I, which until 1996, covered only credit risk. During the crisis, it became apparent that core aspects of the framework are inadequate and, in some cases, set incorrect incentives for banks. For example, credit-dependent instruments were preferentially held in the banking book because of lower capital requirements. As the risk of such instruments is not captured by the existing value at risk (VaR) framework of the trading book and to mitigate the incentive for arbitrage between the trading book and the banking book, an additional incremental risk charge (IRC) must be calculated for unsecuritized credit positions, which includes default and migration risk. Since the VaR framework for quantifying trading book capital is determined on the basis of the previous year's period, it is not surprising that even at the beginning of the crisis, the calculated capital was insufficient to absorb losses. To adjust regulatory capital for a crisis scenario, banks are required to additionally calculate a stressed VaR calibrated on a one-year stress period, which at least doubles the capital requirements. For securitizations, the capital charges of the banking book apply. These changes were implemented by December 31, 2011.

The BCBS had previously explained that these changes focus only on the most pressing issues and that a systematic revision of the entire framework is still pending—the fundamental review of the trading book (FRTB). In May 2012, the first consultative document on the FRTB was published; it was finalized after further consultative documents and standards in 2019, with the rules enforced beginning January 1, 2022. The FRTB includes further measures to reduce regulatory arbitrage and changes to the previous VaR framework to an expected shortfall (ES) framework to account for tail risk. Furthermore, the models of both the standardized approach and the internal models are calibrated for a stress period, and that the newly developed standardized approach are ensured to be a credible fallback of the internal model. A brief description and assessment of the market events are provided in Tab. A.21.

The regulatory treatment of credit risk has also undergone significant tightening. Two capital buffers above the regulatory minimum capital have been implemented. The capital conservation buffer serves to accrue additional capital in good times, which may be utilized during periods of stress. In addition, to prevent procyclicality, national supervisors may require a countercyclical capital buffer to be built up when there are signs of a credit bubble. Due to significant losses on resecuritizations during the GFC, the risk weights under both the standardized approach and internal ratings-based approach (IRBA) increased, as was the case for credit risk exposures resulting from derivatives, repos and securities financing transactions. While under Basel II, bank exposures to central counterparties were not subject to capital requirements, under Basel III, a risk weight of 2% is set. To encourage more derivatives settlement via central counterparties, the BCBS has implemented margin requirements for noncentrally cleared derivatives to reflect the generally higher inherent risk. Having already tightened the capital requirements for resecuritizations, the framework for securitizations is also being strengthened. The standardized approach to securitizations has been tightened, and with regard to the IRBA, the calculated capital requirements may not fall below a floor in relation to the standardized approach.

The standardized approach for credit risk will be revised to be more risk sensitive and more closely aligned with the IRBA. Furthermore, the mechanistic reliance on external ratings for borrower assessment and risk weighting is restricted. Thus, external ratings may be applied only to banks and corporate exposures. Similarly, the use of the advanced and foundational IRBA is also restricted. The advanced IRBA may no longer be utilized for credit exposures for banks, other financial firms, and large corporations. Neither IRBA may be employed for equities. The output floor of both IRBAs is now set to the higher of IRBA risk-weighted assets (RWA) or 72.5% of the RWA of the standardized approach. In Tab. A.22, a brief description and assessment of credit events is given.

While credit and market risk were covered by regulations before the GFC, liquidity regulation is a unique feature of Basel III and can be considered a consequence of the crisis that demonstrated its significance. Due to a lack of confidence, the interbank market came to a standstill, the issuance of new debt became difficult, and banks were forced to sell assets to generate liquidity, which caused their prices to fall and led to write-downs and thus contagion among other market participants. This finding illustrates that liquidity risk is closely linked to credit and market risks. In addition to two quantitative metrics (Pillar 1), supervisory monitoring (Pillar 2) and disclosure and market discipline (Pillar 3) were also tightened, as were the other two financial risks. In temporary terms, short-term and structural liquidity is ensured with the liquidity coverage ratio (LCR) and NSFR under Pillar 1. A brief description and assessment of the liquidity events are provided in Tab. A.23. The event identification process is described in the next section.

2.3.2 Event Identification and Classification

The use of event studies to evaluate the information content of events dates back to Fama et al. (1969) and has long been applied to regulatory events. As Lamdin (2001) discusses in detail, there are issues regarding the use of this method for regulatory changes that must be addressed. A major concern is the exact definition of the event period because ongoing debates may leak information or market participants can anticipate events (Binder, 1985a). Such uncertainty in the event window reduces the power of tests to reject the null hypothesis of no effect (Lamdin, 2001). Therefore, all event days refer exclusively to official BCBS announcements involving consultative documents, standards, sound practices and guidelines for the relevant market, capital or liquidity risk regulation and thus cover initiatives related to Basel II.5, Basel III and Basel IV. This approach ensures that only true information and no rumors or debates influence the calculations to prevent noise. All publications are filtered to reflect the topics of the market, credit and liquidity risk from the beginning of the GFC in 2007 to December 2019.[12] The end of the search period is chosen to allow all relevant changes in regulation to be taken into account and so that the COVID-19 pandemic starting in 2020 does not affect the results. Furthermore, all press releases are reviewed to ensure no significant information is missing in the analysis, which would reduce the power of the tests.[13] All events are evaluated in terms of their information content and their implications for the capital market, including whether they tighten or weaken the existing regulatory framework. Note that the evaluation of each event depends on the prior event since the former announcement can be changed, i.e., tightened or weakened. Events that simply redescribe changes that have already been announced are removed to prevent noise. If an announcement occurred on a weekend, the first available trading day is used as the event date.

Because events corresponding to the market, credit and liquidity regulation are partly announced simultaneously, establishing a causal effect of the specific regulatory announcement type might be misleading. Therefore, analogous to Bruno et al. (2018), tests are performed for the three types of regulation that exclude events that coincide simultaneously with regulatory announcements of the

[12] See `https://www.bis.org/bcbs/publications.htm`.
[13] See `https://www.bis.org/press/pressrels.htm`.

two other types. These tests are referred to as market-only events, credit-only events and liquidity-only events. Although the definition of regulatory capital equally determines the market reaction for credit and market price risk, events that affect only the composition of regulatory capital are removed for this reason.

To further mitigate the influence of noise via nonsignificant events, the information content of all events is investigated via media analysis. Using LexisNexis, international media (Wall Street Journal, Wall Street Journal Europe, Financial Times, International Herald Tribune, International New York Times, American Banker, and The Guardian) are checked to ensure that the events convey new information to the market.[14] To reduce concerns about capital market anticipations, the media analysis is amplified in the week prior to each event. All market, credit and liquidity events and their descriptions can be found in A.

2.3.3 U.S. and EU Implementation of the Basel Accords

The BCBS requires its regulations to apply to "internationally active banks". However, this term is not precisely defined, allowing national authorities some discretion (Basel Committee on Banking Supervision, 2012). Although the BCBS monitors the transposition of its rules into domestic law through the Regulatory Consistency Assessment Program (RCAP), it ensures alignment with minimum regulatory standards only. Market participants may anticipate the extent to which national authorities will implement regulations based on past decisions. For example, under Basel II, only the advanced approach was mandatory for "core banks" in the U.S., while other institutions continued to be regulated exclusively under Basel I. In 2011, only 17 large banks exceeded the regulatory limits based on total assets and on-balance sheet foreign exposure (Basel Committee on Banking Supervision, 2012). In the EU, Basel II was implemented consistently for all institutions (Dierick et al., 2005). The actual implementation of regulations in different jurisdictions does not directly influence market reactions to BCBS announcements, as implementation typically occurs later. However, the example of Basel II demonstrates that banks might anticipate inconsistent future implementation in the EU and the U.S. Therefore, a brief overview of the regulatory institutions and frameworks in both the U.S. and the EU are provided. This overview is followed by an explanation of the implementation of Basel II.5, Basel III, and Basel IV within these jurisdictions. This institutional background then serves as a foundation for deriving hypotheses at both the aggregate and cross-sectional levels for each jurisdiction.

In the U.S., banks can be chartered at either the federal or state level. State-chartered banks are supervised by both federal and state regulators. Consequently, every bank in the U.S. is supervised by one of the federal banking authorities: the Office of the Comptroller of the Currency (OCC), the Federal Deposit Insurance Corporation (FDIC), or the Federal Reserve Board (FRB),

[14]Several keywords are used to evaluate international press coverage of the BCBS announcements; see B.

collectively referred to as U.S. agencies (Basel Committee on Banking Supervision, 2014c). The legal form of a bank, its membership in the Federal Reserve System, and whether it is chartered at the federal or state level determine which of the three U.S. agencies supervises it. In addition to supervision, U.S. agencies are responsible for implementing banking regulations. In the EU, banking regulation is enacted through regulations and directives from the European Parliament and the Council. Directives must be written into national law by member states, while regulations are directly applicable in the context of EU law. Since 2014, the ECB has been responsible for supervising significant institutions under the SSM, while other banks continue to be supervised by national authorities.

Regarding Basel II.5 and its changes to the market risk framework, notable jurisdictional differences exist. In the U.S., the rules apply only to institutions with trading activity (assets and liabilities) that either constitutes ≥ 10% of quarter-end total assets or exceeds ≥ \$1 billion (Office of the Comptroller of the Currency, Treasury and Board of Governors of the Federal Reserve System, 2013). In the EU, the framework was implemented through the Capital Requirements Directive (CRD) III (Directive (EU) 2010/76) and the Capital Requirements Regulation (CRR) (Regulation (EU) 575/2013). Generally, the rules apply without limits to all trading book positions of an institution in accordance with Art. 4 (86) CRR. However, institutions whose on- and off-balance sheet trading book volume is typically less than 5% of the total assets and €15 million and never exceeds 6% of total assets and €20 million are granted relief in the risk calculation according to Art. 94 CRR. Thus, the application in the EU is more restrictive. A further crucial difference is that the Dodd-Frank Act in the U.S. removes the requirement to use credit ratings when assessing the creditworthiness of securities, a provision that also affects credit risk regulation.

The market risk framework was subsequently refined by the FRTB with Basel IV. In the U.S., the proposed rules were released in 2023. They are mandatory for banks with total assets of ≥ \$100 billion (regardless of trading activities), their subsidiary depository institutions and banks with a four-quarter average of trading assets plus trading liabilities ≥ \$5 billion or ≥ 10% of total assets (Office of the Comptroller of the Currency, Treasury et al., 2023). In the EU, the FRTB standards for reporting purposes were implemented with CRR II (Regulation (EU) 2019/876) and CRD V (Directive (EU) 2019/878), while the final rules for the own funds requirements were published in 2024 with the CRR III (Regulation (EU) 2024/1623) and the CRD VI (Directive (EU) 2024/1619). A derogation for small trading book business is granted if the on- and off-balance sheet trading book business is ≤ 5% of the institution's total assets and ≤ €50 million, according to Art. 94 CRR II and CRR III. Similarly to Basel II.5, the application scope of the FRTB is stricter in the EU than in the U.S. The application of the FRTB rules in the EU has been postponed by the Commission until January 1, 2026. This postponement was justified with the intention of not jeopardizing a level playing field because the U.S. implementation is still pending.

Credit risk, which is addressed by Basel III and IV, is treated differently in the U.S. and the EU.

The final U.S. Basel III credit risk framework was released in 2013 and applies to all banks, except for bank holding companies subject to the Board's SBHC Policy Statement (total assets ≤ \$500 million). Some rules, such as the countercyclical capital buffer or the mandatory calculation of capital requirements using internal approaches, apply only to advanced approaches of banks (≥ \$250 billion total assets or ≥ \$10 billion in total consolidated on-balance sheet foreign exposure) and subsidiary depository institutions (Office of the Comptroller of the Currency, Treasury and Board of Governors of the Federal Reserve System, 2013). However, following a general consultation, the U.S. agencies created a comprehensive framework in 2019 for the application of capital and liquidity rules for large banks, and the rules for credit risk were adapted to this framework (Office of the Comptroller of the Currency, Treasury et al., 2019). They are based on four risk-based categories determined by the risk profile to define tailored requirements that increase in stringency on the basis of size- and risk-based indicators (cross-jurisdictional activity, weighted short-term wholesale funding, nonbank assets, and off-balance sheet exposures). Table 1 outlines the characteristics of Category I-IV banks and their additional credit risk requirements, which also apply to their depository subsidiaries. Banks outside these categories follow the general Basel III credit risk rules. Only institutions subject to the Board's SBHC Policy Statement remain exempt from the rules.[15] In the EU, the Basel III credit rules were implemented in 2013 through the CRR and CRD IV (Directive (EU) 2013/36), applying to all banks, which reflects a stricter and more comprehensive approach to their enforcement.

As with the FRTB, there are U.S. proposals from 2023 for the changes to the credit risk framework under Basel IV, which only affect large banks with total assets of ≥ \$100 billion that are assigned to one of the four categories (Office of the Comptroller of the Currency, Treasury et al., 2023).[16] The internal credit risk models will be abolished, requiring banks to calculate capital using both a new standardized approach (expanded risk-based) and the existing standardized approach, with the more conservative result being applied. Consequently, banks in Categories I-IV will follow the same credit risk rules. Additionally, banks in Categories III and IV should recognize elements of accumulated other comprehensive income (AOCI) in regulatory capital, and the countercyclical capital buffer will also apply to Category IV banks. In contrast, Basel IV was already adopted in the EU in 2024 with CRR III and CRD VI, and these regulations will take effect on January 1, 2025. In contrast to the U.S., regulations in the EU generally affect all banks, including the new standardized approach to credit risk. While internal models for credit risk have not been entirely eliminated in the EU, their requirements and application scope are being tightened.

Significant jurisdictional differences also exist in the implementation of the liquidity regulation introduced with Basel III. In the U.S., the agencies published final LCR requirements in October

[15] The threshold for consolidated assets has been raised twice and has been set to ≤ \$3 billion since 2018, as specified in section 207 of the Economic Growth, Regulatory Relief, and Consumer Protection Act (EGRRCPA).

[16] The changes to credit risk regulation are not included in Tab. 1, as they are still proposals.

Table 1: U.S. Implementation of Credit Risk Capital Requirements and Liquidity Rules

Category	Description	LCR	NSFR	Credit Risk
I	G-SIBs and their depository institution subsidiaries	full requirement	full requirement	- G-SIB surcharge - calculate both the advanced and standardized approach - recognize accumulated other comprehensive income (AOCI) in capital - expand the capital conservation buffer by the amount of the countercyclical capital buffer, if applicable
II	≥ \$700 billion in total consolidated assets; or ≥ \$75 billion in cross-jurisdictional activity; do not meet the criteria for Category I	full requirement	full requirement	same as Category I banks without G-SIB surcharge
III	≥ \$250 billion in total consolidated assets; or ≥ \$75 billion in weighted short-term wholesale funding, non-bank assets or off-balance sheet exposure; do not meet the criteria for Category I or II	- full requirement, if ≥ \$75 billion in average weighted short-term wholesale funding - otherwise reduced LCR of 85%	- full requirement, if ≥ \$75 billion in average weighted short-term wholesale funding - otherwise reduced NSFR of 85%	- countercyclical capital buffer - opt out of the requirement to recognize AOCI in capital
IV	≥ \$100 billion in total consolidated assets; do not meet the criteria for Category I, II or III	- reduced LCR of 70%, if ≥ \$50 billion average weighted short-term wholesale funding - otherwise no requirement	- reduced NSFR of 70%, if ≥ \$50 billion in average weighted short-term wholesale funding - otherwise no requirement	generally risk-based capital requirements as banks with ≤ \$100 billion

This table presents the characteristics of U.S. Category I–IV banks, their additional credit risk requirements, and the applicable liquidity regulations.

2014, which took effect in January 2015. Initially, the LCR applied in full only to internationally active banking organizations and their consolidated subsidiaries with assets of ≥ \$10 billion. A bank is considered to be internationally active if the consolidated assets are ≥ \$250 billion or if the balance sheet foreign exposure is ≥ \$10 billion (Basel II threshold). The less strict, so-called modified LCR of 70%, must be complied with by banks that are not internationally active and have ≥ \$50 billion in total assets (Office of the Comptroller of the Currency, Department of the Treasury et al., 2014). Consistent with the application scope of the LCR, a proposal to implement the NSFR was published in 2016 (Office of the Comptroller of the Currency, Department of the Treasury et al., 2016). The liquidity rules were then adapted to the framework based on the risk-based Categories I-IV, and the final NSFR rules were published in 2021 (Office of the Comptroller of the Currency, Department of the Treasury et al., 2021). They are displayed in Tab. 1, and the requirements of parent companies subject to Categories I-III also apply to their depository institution subsidiaries with total consolidated assets of ≥ \$10 bn. Banks that do not meet the criteria are not subject to the LCR and NSFR. In the EU, the LCR was introduced in 2015 and fully applies to all banks in accordance with the CRR, indicating that the requirements in the EU are considerably more stringent. The NSFR was codified in the CRR and fully implemented with CRR II in 2019, becoming a standard in 2021. Generally, the NSFR applies to all EU banks; however, national authorities may permit small and non-complex institutions to adopt a simplified approach (Basel Committee on Banking Supervision, 2022). However, the threshold is restrictive and subject to various criteria, e.g., total assets must be on average ≤ \$5 billion in the last four years.[17] Similar to the LCR, the application scope of the NSFR is broader in the EU than in the U.S., where only the largest institutions need to comply.

In summary, the cross-jurisdictional comparison highlights notable differences in actual implementation. The regulatory scope within the EU is both broader and more stringent across all agreements and for each of the three types of risk. These discrepancies in implementation between the U.S. and the EU lay the foundation for discussing aggregated market reactions and developing the cross-sectional hypotheses.

2.4 Aggregated Market Reactions and Hypotheses for Cross-Sectional Analysis

2.4.1 Market Risk

This section discusses overall market reactions and potential differences between U.S. and EU banks, followed by an analysis of the factors driving potentially heterogeneous responses among banks. To avoid confusion, the terms *negative* and *positive* are used to describe the *direction* of market reactions, although the interpretations differ between stocks and CDSs. A negative stock market reaction indicates a loss for shareholders, whereas it reflects a decrease in CDS spreads, signaling reduced risk for creditors, and vice versa. Both stock and CDS markets may respond positively or negatively to the three financial risks, depending on how creditors and shareholders assess the trade-offs of regulation.

Different implementations in the U.S. and the EU may lead to varied market reactions. The actual implementation in jurisdictions can shape expectations, both ex ante through preceding political discussions and proposals and ex post. One example is Basel III, implemented in the U.S. and the EU in 2013. The 26 credit events considered in this paper span from 2008 to 2019. It is plausible that market participants adjust their expectations in response to BCBS events, such as when pre-2013 negotiations in the U.S. suggested that stricter rules will apply only to large banks. Ex post, these expectations may influence reactions to subsequent BCBS announcements, as similar regulatory implementations are anticipated across jurisdictions. Another example is Basel II, which applied to all EU banks but only to large U.S. banks, thus potentially influencing anticipations for future BCBS accords.

In addition to the overall reaction of markets, the cross-sectional analysis highlights whether certain bank- and jurisdictional-specific variables have a positive or negative effect on stock and CDS market reactions, as it cannot be assumed that all banks react uniformly to regulation. The discussion begins with considerations regarding market risk regulation.

[17] See Art. 4 (1) No. 145 CRR II.

Before potential differences in jurisdictional responses are examined, several key considerations regarding aggregated reactions are outlined. Standard financial theory posits that better capitalized banks with less leverage face lower equity volatility, leading to lower expected returns on debt and stock due to reduced risk (Sarin and Summers, 2016). From this neoclassical perspective, restricted risk-taking reduces future profits. Additionally, equity is costlier than debt due to the tax deductibility of interest, reducing profitability (Moenninghoff et al., 2015). Furthermore, implementing regulation incurs operational costs and requires resources, thereby reducing the funds available for dividend payments. However, arguments for positive stock market reactions exist. Empirical evidence shows that increasing equity can boost bank profitability, especially during crises (Berger and Bouwman, 2013). In addition, Laeven et al. (2016) show that systemic risk decreases with higher capital. If shareholders perceive reduced crisis risks and costs from prudent risk limitations (Miles et al., 2013; Barth and Miller, 2018; Basel Committee on Banking Supervision, 2019), they might respond positively.

Similar arguments apply to the CDS market. The neoclassical view suggests that lower leverage triggers a negative CDS market reaction. Lower spillover risks and greater banking system resilience are also likely to have a negative impact. Conversely, positive CDS market reactions are plausible as well. Sarin and Summers (2016) find higher CDS spreads in the U.S. post-GFC, linked to lower bailout expectations. Similarly, Schäfer et al. (2016) observe increased spreads following financial reforms, especially the Volcker Rule in the U.S., and attribute this finding to reduced bailout expectations. Creditors may view implicit government bailout guarantees in the EU and the U.S. as weakened due to higher capital requirements and the introduction of bail-in debt and resolution frameworks.

The Basel II.5 framework is implemented more restrictively in the EU, where it applies to all institutions; only thresholds for simplified capital requirement calculations exist. In contrast, U.S. regulations apply only to banks with a trading volume of $\geq 10\%$ of total assets or $\geq \$1$ billion. The market events analyzed (see Tab. A.21) span 2007 to 2019, with Basel II.5 implemented in 2013 in both the U.S. and EU. The discussions and proposals leading up to 2013 and beyond influence expectations. For post-2013 events, particularly those related to the FRTB, market participants might anticipate less stringent implementation in the U.S. Notably, while the regulation is already law in the EU, the U.S. has only proposed implementation so far, with a narrower application scope in the EU, similar to Basel II.5.

In addition to the less stringent implementation, the U.S. banking market's structure is characterized by numerous small regional banks that are publicly listed but do not engage in proprietary trading, which may contribute to a U.S. stock market reaction that is milder compared to that of the EU. In contrast, relatively larger banks are listed in the EU and are more likely to engage in trading. Furthermore, the Volcker Rule, enacted as part of the Dodd-Frank Act in 2010, has imposed stringent restrictions on proprietary trading for U.S. banks.[18] Consequently, the risk–return profile of U.S. banks could remain largely unchanged by the Basel' market risk framework, leading to reduced pressure to adhere to these rules. Although a similar CDS reaction is expected in both jurisdictions, as CDSs are generally traded by larger institutions subject to the market risk framework, the Volcker Rule could lead to a less pronounced U.S. reaction.

In the next step, hypotheses for the cross-sectional analysis are developed for U.S. and EU banks. Since both returns and CDS spread changes are closely linked by risk, the same variables are used to explain the heterogeneity in banks' reactions, where applicable. First, the bank-specific variables are operationalized to ensure that they are consistent for U.S. and EU banks before the jurisdictional-specific variables are presented.

The Tier 1 ratio (TIER1_RAT) is the ratio of Tier 1 capital to total RWA and serves as a proxy for capitalization. A higher ratio indicates a lower probability of default (PD), which is expected to negatively impact the CDS market reaction. In contrast, a positive effect on the stock market is anticipated, as banks with higher TIER1_RAT require less additional capital, lowering compliance costs. However, beyond a certain level, the cost of raising additional capital may outweigh its benefits, making the positive effect ultimately negative. Therefore, a quadratic term is included in the stock market estimations to capture this nonlinear relationship.

$\mathrm{H1}_{U.S.,EU,m}$: *Capitalization has a positive but decreasing impact on the stock market reaction and a negative impact on the CDS market reaction.*

Banks' market risk is proxied for the U.S. portfolio by the ratio of derivatives to total assets, DER_ASSET. In contrast, consistent with Fiordelisi and Molyneux (2010) and due to limited data availability, the EU sample uses the more generic ratio of marketable security investments to total assets, SEC_ASSET. It is assumed that higher market risk negatively impacts stock market reactions, as future profitability is expected to decline when banks are forced to assume less risk. To meet requirements, banks with a higher market risk must either raise additional capital or restructure their portfolios. If a bank has significant market risk exposure, it suggests that management relies on generating profits from riskier securities, meaning that its business model is undermined by regulation. In contrast, a positive impact is expected in the CDS market, as these banks continue to face elevated risks.

$\mathrm{H2}_{U.S.,EU,m}$: *Market risk has a negative impact on the stock market reaction and a positive impact on the CDS market.*

In response to the GFC, the Financial Stability Board (FSB) issued a list of G-SIBs in 2011 that are required to hold additional capital and that are subject to stronger supervision. This list is

[18]In 2017, U.S. President Trump initiated a review of the Dodd-Frank Act. On May 24, 2018, EGRRCPA was signed into law. This act raised the threshold for banks considered systemically important from $50 billion to $250 billion, reducing the regulatory burden for many mid-sized institutions, including stress test requirements. Smaller banks with assets of $10 billion or less were granted further relief and exempted from the Volcker Rule.

updated annually with new additions and deletions. A dummy variable, which is 1 for G-SIBs and 0 otherwise, is used.[19] Since G-SIBs must still hold additional capital, shareholders could negatively react to the general tightening of market risk regulation. Furthermore, it is conceivable that G-SIBs engage in more proprietary trading, which could provoke a negative reaction from shareholders. Regarding the CDS market, the risk of G-SIBs is a priori higher, suggesting a positive impact.

$H3_{U.S.,EU,m}$: *G-SIBs have a negative impact on the stock market reaction and a positive impact on the CDS market.*

In the next step, jurisdictional hypotheses are developed based on differences in the implementation and banking system structures. Considering Europe reveals that peripheral GIIPS countries in particular are affected by the sovereign debt crisis. Acharya et al. (2014) provide evidence for a two-way feedback loop between sovereign risk and bank credit risk, demonstrating that a stressed banking sector leads to government bailouts, which increases sovereign credit risk. This outcome, in turn, weakens the banking system because the value of government guarantees and government bonds implicitly decreases. Because domestic bonds capture the majority of banks' sovereign exposure, GIIPS banks are particularly affected (Gennaioli et al., 2018). Thus, they have a higher credit risk than banks outside GIIPS, which implies higher refinancing costs and a higher PD. This condition could also affect the response to market risk regulation because more capital is needed. The EU sample is split with the dummy variable GIIPS, which is 1 if the bank is located in a GIIPS country and 0 otherwise. To examine the feedback loop, the interaction between GIIPS and the sovereign debt crisis (SOV_DEBT) is analyzed, focusing on the interactions between 2010 and mid-2013 (Ricci, 2015; Hobelsberger et al., 2022). A negative impact on the stock market is predicted, whereas a positive impact on the CDS market is assumed because of the higher risk of banks located in GIIPS.

$H4_{EU,m}$: *The feedback loop has a negative impact on the stock market reaction and a positive impact on the CDS market reaction.*

Beyond the feedback loop, several factors suggest differing responses between GIIPS banks and non-GIIPS banks. One argument is rooted in fire sales, as the sale of sovereign bonds is identified as a major driver of systemic risk (Greenwood et al., 2015). Because GIIPS banks hold riskier sovereign bonds and are riskier a priori, they could try to sell their sovereign exposure in a crisis, which could be exacerbated by market risk regulation, thus increasing their PD. Furthermore, GIIPS banks may find it difficult to find counterparties for derivatives due to their sovereign exposure. The discussion starting in 2015 on the abolition of the preferential treatment of sovereign exposures in the banking and trading books could also contribute to a tightening of the market reaction of GIIPS banks (Basel Committee on Banking Supervision, 2017).[20]

[19] In general, G-SIBs are classified into different buckets. No distinction is made in the context of this work. For consistency, the identified G-SIBs in 2011 are classified as G-SIBs prior to 2011.

[20] Ultimately, these considerations were not realized. Only disclosure requirements for sovereign exposures were

Unfortunately, due to unavailable granular data on trading assets and liabilities, a plausible approximation of whether a U.S. bank is subject to the market risk framework and the formulation of a specific hypothesis cannot be carried out.

2.4.2 Credit Risk

As the regulatory treatment of market and credit risk is comparable due to higher capital ratios for RWA, the arguments for aggregated market reactions from the previous section are referenced. Basel III credit risk rules apply to all U.S. banks, except for SBHCs.[21] Some requirements are mandatory only for large banks, with the definition evolving over time. Since 2019, these banks are generally those with total assets of ≥ $250 billion (see Tab. 1). Basel IV changes in the U.S. are still in the proposal stage and exclusively target large banks. In contrast, the EU applies the Basel III credit risk framework to all banks without exception, and Basel IV has already been implemented.

It is assumed that EU banks have a stronger stock market reaction due to the stricter implementation without exceptions or size thresholds, and partly because Basel IV, which will be mandatory only for large U.S. banks, has not yet been implemented in the U.S. Although the implementation of CRR III and CRD VI in the EU and the U.S. proposal fall outside the credit events period (2008-2019), market expectations shaped by previous divergent implementations and negotiations in these regions can still influence reactions to BCBS announcements. A similar response in the CDS market is expected, comparable to market risk regulation discussions, as CDSs typically cover the largest banks, which are treated similarly in both the U.S. and the EU. However, the U.S. faces delays in implementing Basel IV, which could be anticipated.

The determinants of market responses are somewhat similar for market and credit risk as the regulatory treatment is partially consistent, which is why some hypotheses are the same. The influence of capitalization is assumed to be analogous to that of market risk regulation.

$\text{H1}_{U.S.,EU,c}$: *Capitalization has a positive but decreasing impact on the stock market reaction and a negative impact on the CDS market reaction.*

The ratio of total loans to total assets (LOAN_ASSET) serves as a proxy for credit risk. Banks that face higher credit risk are required to secure additional capital, leading to increased costs. Additionally, new regulations can impose restrictions on risk-taking, which can curtail future profits. Consequently, a negative impact on the stock market is anticipated. Conversely, in the CDS market, a positive impact is expected, reflecting the heightened credit risk in comparison to other banks.

$\text{H2}_{U.S.,EU,c}$: *Credit risk has a negative impact on the stock market reaction and a positive impact*

implemented, which are mandatory only when required by national supervisors.

[21] The number of these holding companies supervised by U.S. agencies on December 31, 2012, was substantial, totaling 3,802 (Office of the Comptroller of the Currency, Treasury and Board of Governors of the Federal Reserve System, 2013).

on the CDS market.

Another aspect of credit risk regulation involves the cost of risk, measured by the ratio of loan loss provisions to total loans (PROV_LOAN) (Brissimis et al., 2008). These costs are expected to rise due to regulation, likely leading to a negative effect on stock market reactions and a positive effect on CDS market reactions.

$H3_{U.S.,EU,c}$: *Credit risk costs have a negative impact on the stock market reaction and a positive impact on the CDS market reaction.*

Similar to market risk, the influence of banks as G-SIBs is analyzed for credit risk, with the expected direction of impact being consistent.

$H4_{U.S.,EU,c}$: *G-SIBs have a negative impact on the stock market reaction and a positive impact on the CDS market.*

Alongside the bank-specific hypotheses, the jurisdictional hypotheses are examined in the next step. As in the analysis of EU market risk determinants, the mechanism of the feedback loop is tested.

$H5_{EU,c}$: *The feedback loop has a negative impact on the stock market reaction and a positive impact on the CDS market reaction.*

U.S. credit risk rules are not binding for SBHCs. To capture differences in market reactions between SBHCs and affected institutions, a dummy variable AFF_BANK_c is constructed that is 0 for SBHCs and 1 otherwise. The size-based regulatory thresholds determining when a bank holding company is exempt from regulation have changed over time, leading to the following specification: a bank holding company is classified as SBHC if its total assets are ≤ \$500 million prior to October 23, 2013 (the day before a bill of Public Law 113-250 was introduced in the House, which raises the threshold to ≤ \$1 billion), ≤ \$1 billion between October 23, 2013 and November 15, 2017 (the day before a bill of Public Law 115-174 (EGRRCPA) was introduced in the Senate that raised the threshold to ≤ \$3 billion), and ≤ \$3 billion on November 16, 2017.[22] Because CDSs are available for large banks only, the hypothesis cannot be tested for creditors.

$H5_{U.S.,c}$: *AFF_BANK_c negatively impacts stock market reactions.*

2.4.3 Liquidity Risk

In terms of aggregated market reactions to liquidity risk, the considerations and arguments differ from those related to market and credit risk. Unlike the latter, liquidity risk is not regulated through capital requirements but rather by mandating that banks hold a higher proportion of liquid assets and avoid structural funding mismatches. A negative stock market reaction is plausible, as banks prioritize profit maximization when selecting assets and funding, which is hindered by liquidity regulation (Bruno et al., 2018). This situation creates opportunity costs, as banks must hold

[22]Exemptions apply exclusively to holding companies, not to banks. As described above, SBHCs are approximated with a size-based threshold. In addition to these thresholds, bank holding companies must meet additional qualitative criteria, which, however, cannot be properly mapped with the available data.

lower-yielding assets, such as government bonds, rather than more profitable loans or securities to meet liquidity requirements. In addition, liquidity introduces moral hazard to management (Jensen, 1986).

Nevertheless, there are arguments suggesting a positive stock market reaction. The GFC highlighted the severe impact of liquidity risk, including systemic risk and spillover effects, which the LCR and NSFR aimed to address (Basel Committee on Banking Supervision, 2013, 2014a). Additionally, global standards offer convergence benefits (Bruno et al., 2018).

The previous arguments are relevant for CDSs as well, and a negative market reaction can be expected if liquidity regulation mitigates the risks of excessive profit maximization. This expectation holds if the regulatory goals of reducing systemic risk due to liquidity shortages and spillover effects are met. Conversely, a positive CDS market reaction is also conceivable. Myers and Rajan (1998) analyze the "dark side" of liquidity. Their model shows that higher liquidity limits a firm's ability to commit to strategies that protect creditors. Another argument concerns reduced bailout expectations.

Although the scope of the LCR and NSFR has evolved over time, both metrics have always been intended for the largest U.S. banks. In contrast, the EU applies both metrics to all banks. Consequently, the stock market reaction in the EU is expected to be stronger than that in the U.S., where the rules are not relevant to shareholders of smaller banks. A weaker reaction is further supported by the better liquidity situation of U.S. banks during and after the GFC compared with their EU competitors (European Banking Authority, 2012; Dietrich et al., 2014). Since large U.S. banks are subject to liquidity requirements and CDSs are available primarily for these banks, a comparable CDS market reaction in both jurisdictions is assumed, albeit possibly somewhat weaker due to the better liquidity situation of U.S. institutions. Building on Bruno et al. (2018) and Simion et al. (2024), cross-sectional hypotheses are developed, and since they examine the economic rationale of regulation, the LCR and NSFR are first addressed, which aim to ensure a bank's short-term liquidity and prevent structural funding mismatches. As shown in Tab. A.23, the liquidity events span from 2008 to 2017. The LCR was introduced in 2015, followed by the NSFR in 2018 (Basel Committee on Banking Supervision, 2014b, 2015). Hence, neither ratio is reported by banks for all liquidity events. Furthermore, since the necessary data for calculating the ratios were not yet published in earlier balance sheets, plausible approximations must be used across all events for consistency (Bruno et al., 2018). Due to the significantly divergent jurisdictional implementation, the hypotheses for the U.S. and the EU are formulated separately, starting with the EU.

The variable LCR_PROXY represents the ratio of liquid assets to demand deposits and short-term funding. Banks with more liquid assets are better positioned to meet LCR requirements, reducing the pressure to restructure their assets. Therefore, a higher LCR_PROXY should positively affect stock market reactions and negatively impact CDS market reactions.

$H1_{EU,l}$: *Banks with more liquid balance sheets have a positive impact on the stock market reaction and a negative impact on the CDS market.*

The NSFR conceptually aligns with the "golden rule of banking" by limiting maturity transformation. This situation arises if the stability and long-term nature of the liabilities are sufficient to cover the outflows of assets. As outlined in Art. 26 (Basel Committee on Banking Supervision, 2014a), regulatory capital is eligible as available stable funding at 100%, which also applies to demand deposits of retail and small business customers in a range of 90% to 95%. Banks relying heavily on short-term wholesale funding may struggle to meet these requirements, as their situations are considered less stable. Compliance is also challenging for banks with minimal regulatory capital, forcing them to raise additional equity and restructure their funding. The variable NSFR_PROXY is defined as the ratio of the sum of total equity, long-term funding and customer deposits to total assets. A higher ratio indicates a smaller funding mismatch, which is expected to positively impact the stock market and negatively affect the CDS market. The reason is that banks with smaller mismatches face lower liquidity risk and reduced compliance costs.

H2$_{EU,l}$: *A lower funding mismatch has a positive impact on the stock market reaction and a negative impact on the CDS market.*

The charter value of a bank can be defined as the value that would be foregone due to insolvency and includes, e.g., reputation, monopoly rents or economies of scale (Acharya, 1996). Since those values cannot be sold if a bank is insolvent, banks with higher charter values have a lower incentive to risk failure (Keeley, 1990). Ratnovski (2009) examines the relationship between banks' liquidity decisions and their charter values and finds a positive correlation. This result implies that banks protect their charter values by maintaining adequate liquidity (Bruno et al., 2018). Since banks base their liquidity on the likelihood of a bailout (generate short-term bailout rents with low liquidity level vs. preserve the charter value with high liquidity and long-term rents) and liquidity regulation reduces this probability, banks with higher charter values will choose higher liquidity (Bruno et al., 2018). Charter values should have a positive impact on the stock market reaction and a negative impact on the CDS market reaction because the PD decreases with higher levels of liquidity. The ratio of customer deposits to total assets (DEP_ASSET) is the proxy for a bank's charter value (Keeley, 1990; Goyal, 2005).

H3$_{EU,l}$: *A higher charter value has a positive impact on the stock market reaction and a negative impact on the CDS market reaction.*

Regarding the EU sample, as in the previous sections, the feedback loop between sovereign credit risk and banks' credit risk is assumed to negatively impact the stock market reaction while positively affecting the CDS market. This expectation is due to higher refinancing costs and a higher PD.

H4$_{EU,l}$: *The feedback loop has a negative impact on the stock market reaction and a positive impact on the CDS market reaction.*

In contrast to the EU, U.S. liquidity rules were always intended only for large banks. To capture this design, two dummy variables are constructed following Sundaresan and Xiao (2024): MOD_AFF_l is set to 1 for all banks with total assets ≥ \$50 billion and < \$250 billion (banks subject to less stringent liquidity requirements), and 0 otherwise, and FULL_AFF_l is set to 1 for banks with total assets ≥ $250 billion, and 0 otherwise (banks that must meet the full requirements). Since the liquidity events under consideration extend until 2017, this categorization is plausible, as the tailoring of capital and liquidity rules, with adjusted requirements for banks, was discussed and implemented at a later stage. Because the LCR and NSFR apply only to large banks, MOD_AFF_l and FULL_AFF_l are interacted with LCR_PROXY and NSFR_PROXY. Both positive and negative coefficients are conceivable. A positive effect could be explained analogously to the previous arguments regarding the impact on the EU stock market, as higher compliance results in lower costs to the regulatory requirements. Conversely, a negative effect is conceivable because U.S. banks had higher liquidity levels, making affected U.S. banks less willing to adjust their assets (LCR) and funding (NSFR). Another argument for a negative effect is that U.S. implementation penalizes large banks, while institutions not subject to the rules (which represent the majority) gain a competitive advantage.

H1_A$_{U.S.,l,\ stock}$: *Affected banks have a positive impact on the stock market reaction with more liquid balance sheets and a lower funding mismatch.*

H1_B$_{U.S.,l,\ stock}$: *Affected banks have a negative impact on the stock market reaction with more liquid balance sheets and a lower funding mismatch.*

Similar to the cross-sectional analysis of credit regulation, the impact of the affected banks on the CDS portfolio cannot be assessed, as it includes exclusively large banks. Therefore, the effect of the LCR and NSFR is examined without an interaction term. A negative impact on CDS spreads is assumed due to the increased resilience to liquidity shocks and funding risks.

H1$_{U.S.,l,CDS}$: *Banks with more liquid balance sheets have a negative impact on the CDS market reaction.*

H2$_{U.S.,l,CDS}$: *A lower funding mismatch has a negative impact on the CDS market reaction.*

Additionally, the mechanism of the charter value is examined analogously to the EU estimation for both stock and CDS markets.

H2$_{U.S.,l,stock}$: *A higher charter value has a positive impact on the stock market reaction.*

H3$_{U.S.,l,CDS}$: *A higher charter value has a negative impact on the CDS market reaction.*

2.5 Methodology

2.5.1 Data

All data used in this paper are sourced from Refinitiv Eikon and Bloomberg. To capture capital market reactions, daily closing prices of stocks and end-of-day CDS mid-spreads, written on senior unsecured debt, are gathered for all available EU and U.S. banks.[23] To illustrate the effects on

[23] The EU sample consists of banks from Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Netherlands, Poland, Portugal, Romania, Spain, Sweden, and the United Kingdom (UK). The countries of origin in the EU portfolios vary depending on the type of regulation

debt, it is also possible to use bonds. Nevertheless, using CDS spreads is recommended for several reasons, e.g., Longstaff et al. (2005); Bessembinder et al. (2009); Ericsson et al. (2009). CDSs with a five-year maturity are the most widely traded and most liquid, which is why they are used. To generate reliable samples, in line with Simion et al. (2024), only banks' stocks that meet both of the following criteria are considered: (1) returns must be available every day in the event window, and (2) the sum of unavailable observations and zero returns must not exceed 50% of the estimation window. A bank's CDS spread changes are considered only if (1) they are available in the event window each day, and (2) unavailable observations do not exceed 50% of the estimation window.[24] The criterion for inclusion in the portfolio is weakened for CDSs because zero changes in CDS spreads are not problematic in the estimation window. A zero change in stock returns suggests nontrading, with CDSs being available only on a day when a new contract has been closed. A zero change in CDS spreads therefore does not imply nontrading but rather that the risk has not changed from the creditor's perspective. In a further step, insolvent and nationalized banks are removed. After the banks that fulfill the above requirements are identified for each event, an intersection is formed for each regulatory category to generate balanced panels of bank returns and CDS spread changes. This step leads to a significant reduction in the sample size, but with an unbalanced panel, the aggregation of portfolio returns and CDS spread changes could not be properly performed. The results of the selection process are provided in Tab. 2.

Table 2: Number of Included Banks per Regulatory Category and Financial Instrument

Type	**EU**		**U.S.**	
	Stocks	CDS spreads	Stocks	CDS spreads
Market risk	66	20	220	8
Credit risk	72	27	218	8
Liquidity risk	72	18	222	8

This table presents the number of included banks for each regulatory category and financial instrument in the EU and the U.S. after applying the liquidity criteria.

2.5.2 *Event Study Design*

To examine the capital market reactions, an event study approach is employed. Following the methodological literature, e.g., Brown and Warner (1985); MacKinlay (1997), abnormal returns

and for stocks and CDSs. The UK left the EU on January 31, 2020; however, all events examined in this paper occurred prior to this date.

[24]Returns and CDS spread changes are computed as logarithmic differences of stock prices and CDS spreads, respectively.

$AR_{i,t}$ are calculated using the market model (Sharpe, 1963).[25] $AR_{i,t}$ is the abnormal return of bank i at time t in the event window and is calculated as follows

$$AR_{i,t} = R_{i,t} - (\hat{\alpha}_i^r + \hat{\beta}_{1,i}^r R_{m,t}), \tag{3}$$

where $R_{i,t}$ is the actual return of bank i at time t and $R_{m,t}$ is the market index return. The subtrahend corresponds to the expected returns with parameters calculated in the estimation window using OLS. Supranational and broad stock indices are less subject to bias than national indices because of the reduced correlation of financial and nonfinancial firms within a specific country and the correlation of banks in different countries (Ongena et al., 2003). Therefore, the effect of bank regulation should be less visible because the influence of banks is lower due to the wide diversification and more constituents. Thus, the abnormal effect due to regulatory announcements can be determined in a more isolated way. Given these considerations, the MSCI World index is used. To avoid making the results contingent on the choice of index, the analyses are additionally carried out for the EU with the MSCI Europe index and for the U.S. with the MSCI USA index.

In contrast, the literature provides evidence that many factors, mainly macroeconomic factors (Collin-Dufresne et al., 2001; Ericsson et al., 2009), provide explanatory power for CDS spreads. Therefore, consistent with prior research (Couaillier and Henricot, 2023), the factor model proposed by Andres et al. (2021) is used to estimate abnormal CDS spread changes $\Delta AS_{i,t}$ for bank i at time t in the event window

$$\Delta AS_{i,t} = \Delta S_{i,t} - (\hat{\alpha}_i^s + \hat{\beta}_{1,i}^s \Delta S_{index,t} + \hat{\beta}_{2,i}^s Level_t + \hat{\beta}_{3,i}^s Slope_t + \hat{\beta}_{4,i}^s \Delta Vola_t). \tag{4}$$

The minuend $\Delta S_{i,t}$ corresponds to the actual CDS spread change of bank i at time t. The subtrahend reflects the calculation of the expected CDS spreads of bank i at time t, whereby the parameters are estimated in the estimation window using OLS. The change in the CDS market index is $\Delta S_{index,t}$.[26] Unfortunately, there is no global CDS index. Hence, the iTraxx Europe 5-years index is selected for the EU CDS market, and the iTraxx CDX IG 5-years index is selected for the U.S. CDS market.[27] $Level_t$ is the level of the risk-free interest rate (proxied by the 5-year interest rate swap rate with reference to the 3M EURIBOR in Europe and the 5-year interest rate swap rate with reference to the 3M LIBOR in the U.S.). $Slope_t$ is the slope of the risk-free interest rate (proxied by the difference in the 10- and 2-year swap rate with the above specification in Europe and the U.S.). $\Delta Vola_t$ is the daily

[25] The market model is not extended with further regressors to form a multifactor model, as they provide only marginal additional explanatory power (MacKinlay, 1997).

[26] For reasons of robustness, $\Delta AS_{i,t}$ are additionally calculated using the standard single-index model as follows: $\Delta AS_{i,t} = \Delta S_{i,t} - (\hat{\alpha}_i^{si} + \hat{\beta}_{1,i}^{si} \Delta S_{index,t})$.

[27] Since both indices have missing values, the last observation carried forward method is used to fill data gaps for up to five missing observations before calculating the index returns.

change in the equity implied volatility (proxied by the VSTOXX in Europe and the VIX in the U.S., respectively). Considering events over several years and potential parameter instability, a separate estimation window is constructed for each event. A trade-off exists in selecting an appropriate estimation window: as the period lengthens, the model parameter accuracy improves, but so does the probability of parameter changes and overlapping events. As the events coincide with the GFC and the European sovereign debt crisis, a 150-day estimation window preceding each event is used to balance accuracy and bias in coefficient estimates.

To further account for such a bias, market-adjusted returns $MAR_{i,t}$ and CDS spread changes $\Delta MAS_{i,t}$ (Fuller et al., 2002; Andres et al., 2021) are computed directly in the event window as the difference between bank's i return $R_{i,t}$ and the return $R_{m,t}$ of a market index as well as between the bank's CDS spread change $\Delta S_{i,t}$ and the CDS spread change of the CDS index $\Delta S_{index,t}$

$$MAR_{i,t} = R_{i,t} - R_{m,t}, \tag{5}$$

$$\Delta MAS_{i,t} = \Delta S_{i,t} - \Delta S_{index,t}. \tag{6}$$

Although no estimation window is required and only the first liquidity criterion of Sec. 2.5.1 is binding, the same banks are considered for reasons of comparability. Confounding events in the event window are more concerning as they directly bias the calculation of the abnormal effect. Since this problem increases with a larger event window, the latter is limited to three days ranging from t_{-1} to t_{+1} and centered on the event date t_0. Moreover, short event windows with daily data enhance significance test power, reducing the probability of a type II error (Schäfer et al., 2016). In the event window, the corresponding cumulative abnormal returns $CAR_{i,t}$, cumulative market-adjusted returns $CMAR_{i,t}$, cumulative abnormal CDS spread changes $\Delta CAS_{i,t}$ and cumulative market-adjusted CDS spread changes $\Delta CMAS_{i,t}$ are calculated for each bank as follows

$$CAR_{i,t} = \sum_{t=t_{-1}}^{t_{+1}} AR_{i,t}, \tag{7}$$

$$CMAR_{i,t} = \sum_{t=t_{-1}}^{t_{+1}} MAR_{i,t}, \tag{8}$$

$$\Delta CAS_{i,t} = \sum_{t=t_{-1}}^{t_{+1}} \Delta AS_{i,t}, \tag{9}$$

$$\Delta CMAS_{i,t} = \sum_{t=t_{-1}}^{t_{+1}} \Delta MAS_{i,t}. \tag{10}$$

2.5.3 *Aggregated Market Reactions and Block Bootstrap Significance Test*

The starting point of the calculation of aggregated market reactions and their significance with respect to the three types of regulation are $CAR_{i,t,x}$, $CMAR_{i,t,x}$, $\Delta CAS_{i,t,x}$ and $\Delta CMAS_{i,t,x}$, with

$x \in \{m, c, l\}$ (m = market risk, c = credit risk and l = liquidity risk). To avoid redundancies, the additional procedure is explained on the basis of $CAR_{i,t,x}$, beginning with calculating the overall effects. For each event and separately for each type of regulation, the average cumulative abnormal return $\overline{CAR}_{x,e}$ is calculated based on equally and market-weighted portfolios. The latter method assigns more weight to larger banks, and the $CAR_{i,t,x}$ are weighted with their proportional market value in the portfolio as of the last trading day of the previous quarter (Armstrong et al., 2010).[28] Events that weaken regulation compared with the initial proposal are multiplied by -1 because it is not appropriate to aggregate the untreated $\overline{CAR}_{x,e}$ over several events (Armstrong et al., 2010). According to the type of regulation, $\sum \overline{CAR}_x$ is calculated as the sum of the $\overline{CAR}_{x,e}$ over all events to capture the total effect of market, credit and liquidity regulation.

Because the number of events is never greater than 26, significance cannot be reliably evaluated using common tests. Therefore, following Armstrong et al. (2010), block bootstrap simulations are employed, which is explained using market risk regulation and the EU stock market as an example.

All days within the range of t_{-2} to t_{+2} to the actual events are excluded from the simulation of nonevent days. This step ensures that only nonevent trading days are considered with corresponding nonevent windows that do not overlap with the actual event windows.[29] Therefore, the simulated data fit the distribution under the null hypothesis that no market risk regulation occurs. Because return distributions are often nonstationary (Bey (1983); Hsu (1984)), 15 nonevent days are randomly drawn such that they mimic the year-by-year distribution of market events (Armstrong et al., 2010) and that the nonevent windows do not overlap. Thus, one nonevent day is drawn from 2007, one nonevent day is drawn from 2008, two nonevent days are drawn from 2009, etc.; see Tab. A.21. For each simulated nonevent day, the $\overline{CAR}_{m,e}$ are computed based on equally weighted and market-weighted portfolios. Then, the assumed pattern regarding the tightening and weakening of regulation is applied to nonevents. This simulation of 15 nonevents is repeated 1000 times. The sum of the $\overline{CAR}_{m,e}$ over all 15 nonevents is computed for each of the 1000 simulations to form 1000 nonevent $\sum \overline{CAR}_m$. This procedure does not rely on any distributional assumptions, and a two-sided test is performed because the direction of the expected reactions is unclear; see Sec. 2.4. For this purpose, p values are calculated according to the number of cases for which the actual event $\sum \overline{CAR}_m$ is larger or smaller than the 1000 nonevent $\sum \overline{CAR}_m$.

The bootstrap procedure of the market-only events is analogously performed. Only the pattern of the annual distribution changes, and the number of events decreases from 15 to eleven.

To statistically rule out anticipation effects by information leakage and to prevent the results from being driven by overall short-run market trends near the event days, following Bruno et al. (2018),

[28] For the EU samples, the market values in the respective national currency are first converted into euros.

[29] Since a three-day nonevent window is constructed from the simulated nonevent days, t_{-2} and t_{+2} of the actual events need to be excluded. If t_{-2} (t_{+2}) were drawn, then the constructed nonevent window would contain t_{-1} (t_{+1}) and thus overlap with the actual event window.

placebo events are constructed five trading days before the actual events and tested for significance.

2.5.4 Cross-Sectional Analysis

In a further step, which bank- and country-specific characteristics explain the variation in EU and U.S. market responses are analyzed. The models are explained using $CAR_{i,t}$ and $\Delta CAS_{i,t}$, with the regressions analogously computed using $CMAR_{i,t}$ and $\Delta CMAS_{i,t}$ as dependent variables. According to the type of regulation, $CAR_{i,t}$ and $\Delta CAS_{i,t}$ are regressed on a vector of bank- ($\mathbf{BANK}_{i,t}$) and country-specific ($\mathbf{COUNTRY}_{i,t}$) variables, where the variables depend on the type of regulation and the jurisdiction, which is why the regressions are separately run for each financial risk and separately for EU and U.S. banks (see Sec. 2.4).[30] The most recent available accounting data before each event is presented in United States dollar (USD) and euros, respectively, meaning either quarterly or annual figures. The vector $\mathbf{CONTROL}_{i,t}$ includes the control variables, leading to the following models

$$CAR_{i,t} = \alpha^r + \boldsymbol{\beta}^{r\prime}\mathbf{BANK}_{i,t} + \boldsymbol{\gamma}^{r\prime}\mathbf{COUNTRY}_{i,t} + \boldsymbol{\delta}^{r\prime}\mathbf{CONTROL}_{i,t} + \epsilon^r_{i,t}, \tag{11}$$

$$\Delta CAS_{i,t} = \alpha^s + \boldsymbol{\beta}^{s\prime}\mathbf{BANK}_{i,t} + \boldsymbol{\gamma}^{s\prime}\mathbf{COUNTRY}_{i,t} + \boldsymbol{\delta}^{s\prime}\mathbf{CONTROL}_{i,t} + \epsilon^s_{i,t}. \tag{12}$$

$\mathbf{CONTROL}_{i,t}$ includes the level of profitability (measured as the return on assets (ROA)) and the level of cost efficiency (measured by the cost-to-income ratio (COST_INC)); see Fiordelisi and Molyneux (2010). Furthermore, the natural logarithm of total assets is included to control for the size (SIZE). To capture the impact of regulation over time, the sample period is divided into four subperiods. Following Aït-Sahalia et al. (2012) and Ricci (2015), the first period is labeled the "subprime crisis" and ranges from June 1, 2007, to September 14, 2008, the day before Lehman Brothers declared bankruptcy. The second period is referred to as the "global financial crisis" and ranges from September 15, 2008, to May 1, 2010, which is the day before the start of the European sovereign debt crisis with a €110 billion bailout package for Greece. The third period starts on May 2, 2010, and ends on June 30, 2013, which is labeled the "sovereign debt crisis" (Ricci, 2015; Hobelsberger et al., 2022). The last period is labeled "ex post crisis" and ranges from July 1, 2013, to the last event. Dummies of these periods are included as controls in the U.S. estimates, while in the EU estimates, the sovereign debt crisis is interacted with GIIPS as an explanatory variable. Because events for the three financial risks were announced at different times, not all periods occur for all regulatory categories. To avoid perfect multicollinearity, one period is always dropped.

Again, dependent variables are multiplied by -1 if the event is associated with a reduction in regulatory intensity. The absence of multicollinearity is checked using variance inflation factors

[30] Analyzing the cross-sectional determinants of abnormal returns and CDS spread changes using a 2-stage approach is common in the finance literature: e.g., Moenninghoff et al. (2015); Carboni et al. (2017); Bruno et al. (2018); Pancotto et al. (2020); Simion et al. (2024).

(VIFs).[31] Equations are estimated using random effects with clustered standard errors at the bank level because time-invariant variables (GIIPS) are included in EU estimations. Descriptive statistics of independent variables are provided in C.

2.5.5 *Handling Confounding Events*

In any event study, two crucial considerations are event selection and avoiding bank-specific confounding events in the event window, as both can introduce bias. The former problem is mitigated through careful event selection (see Sec. 2.3.2). Regarding the latter problem, all event windows are checked for bank-specific news with LexisNexis.[32] During many events, bank-specific news occur that affect both the aggregated market reactions and the cross-sectional analysis.

To validate the results of the cross-sectional analysis, the regressions are recomputed, omitting banks in each event with confounding news. The results do not change the conclusions and can be provided upon request. The impact on aggregated market reactions is difficult to account for because balanced stock and CDS portfolios are constructed. This fact implies that a bank would no longer be part of the portfolio even if it is missing only in one event due to bank-specific news (because the intersection of banks is formed over all events), which leads to a significant reduction in sample size, especially for a higher number of events. Bank-specific confounding events are likely to play a minor role in the calculation of overall effects, given that messages randomly occur and the sample is sufficiently large. Against this background, the results for stock markets should be sufficiently robust. However, for CDS markets, due to smaller samples, especially for U.S. portfolios with eight banks, and the higher responsiveness of professional creditors, it is important to pay close attention to whether the overall effect could be biased. Due to higher sensitivity, outliers are more likely, which, combined with a smaller sample over which the effect is averaged, introduces a higher risk that the overall effect is biased. Close attention is given to this issue when discussing CDS market reactions.

2.6 *Discussion*

2.6.1 *Market Risk*

For the stock market analysis, results based on the MSCI World index are used. Only when significant deviations occur are the MSCI Europe and MSCI USA indices considered as proxies for the stock market portfolio (see D). The EU CDS market reaction is measured using the iTraxx Europe 5-year index, while the iTraxx CDX IG 5-year index is used for the U.S. market. Results

[31] Calculated VIFs indicate the absence of multicollinearity. The results can be provided upon request.

[32] Following Bruno et al. (2018), the following keywords are utilized: dividends, earnings, CEO, losses, write-downs, restatement, downgrade, rating, fraud, annual report, manipulate, inspection, restructuring, M&A, merger, acquisition, stock split, dilution, fired, restructuring, issue, and takeover.

from the single-index model are presented only if notable differences arise (see D).[33] The study first addresses the impact of market risk regulation.

The EU stock market responds negatively, with equally weighted portfolios experiencing an overall effect of -0.1476 ($\sum \overline{CMAR}_{m\_ew}$) and -0.1182 ($\sum \overline{CAR}_{m\_ew}$), both significant at the 5% and 10% levels. The market-weighted reactions, $\sum \overline{CMAR}_{m\_mw}$ at -0.2016 and $\sum \overline{CAR}_{m\_mw}$ at -0.1693, are significant at the 5% level. Larger banks, which are more likely to engage in proprietary trading, may explain these stronger reactions.[34] When market events announced alongside credit and liquidity events (events 3, 4, 8, and 13) are excluded, no values are significant. This finding likely stems from the excluded events' importance, as they were announced at the outset of market risk regulation, during a time when the upcoming rules were anxiously awaited. Moreover, they introduced significant changes, drawing considerable media attention. Events 3 and 4 introduced adjustments to capital requirements for incremental risk in the trading book, along with a new stressed VaR measure that effectively doubles the capital requirements. In contrast, credit events 2 and 3, which coincided with market events 3 and 4, had a lower impact on credit risk regulation, as resecuritizations were merely assigned higher risk weights. To substantiate this finding, the market reaction is recalculated using the four excluded market events (3, 4, 8, and 13). Distinct negative reactions of -0.0944 ($\sum \overline{CMAR}_{m\_ew}$), -0.0879 ($\sum \overline{CAR}_{m\_ew}$), -0.1665 ($\sum \overline{CMAR}_{m\_mw}$), and -0.1681 ($\sum \overline{CAR}_{m\_mw}$) are observed. The equally weighted reactions are significant at the 5% level, while the market-weighted ones are significant at the 1% level. Event 3 largely drives the overall effect, where the BCBS published proposals for the IRC and a stressed VaR. Given this impact, the BCBS should carefully consider market conditions and financial stability when making such announcements. The conclusion is that EU bank shareholders are facing wealth losses.

In contrast, U.S. reactions are insignificant, indicating that shareholders are less affected. The differences in stock market reactions between the U.S. and the EU can be attributed to the EU's stricter implementation of regulations. Additionally, small regional banks in the U.S., which typically do not engage in proprietary trading, are often publicly listed and included in the sample, whereas larger banks in the EU tend to be capital market-oriented. This difference is reflected in the significantly larger market capitalization in the EU compared with the U.S., which could also account for the positive reactions observed in the equally weighted U.S. portfolio, while the market-weighted reactions remain negative.[35] Another explanation is that the risk–return profile

[33] The number of banks in the EU CDS portfolio is lower in terms of market-weighted reactions because IKB Deutsche Industriebank AG, Coöperatieve Rabobank U.A., and Bayerische Landesbank are not publicly listed: $m = 19$, $c = 25$, and $l = 16$.

[34] Effect size and significance are more pronounced for calculations with the MSCI Europe index.

[35] To substantiate this finding, the mean and median market capitalizations are calculated for each of the 15 events. The average mean market capitalization is approximately $18.1 billion for the EU sample and $6.2 billion for the U.S. sample. The disparity is even more pronounced when examining the average median values, with the EU at $12.7 billion and the U.S. at approximately $339 million.

of U.S. banks has not changed due to Basel regulations, primarily because of the existing Volcker Rule.

The EU CDS reaction is consistently negative for all market and market-only events, none of which is significant. However, examining the placebo events reveals positive abnormal CDS spread changes of 0.4644 ($\sum \overline{\Delta CMAS}_{m\_ew}$), 0.4149 ($\sum \overline{\Delta CAS}_{m\_ew}$), 0.5742 ($\sum \overline{\Delta CMAS}_{m\_mw}$), and 0.5635 ($\sum \overline{\Delta CAS}_{m\_mw}$). Among these, $\sum \overline{\Delta CAS}_{m\_ew}$ is significant at the 5% level, while the other three values are significant at the 1% level. The analysis of market-only placebo events confirms these findings. These values are driven mainly by placebo event 12. Further analysis reveals that a report from Commerzbank, which indicated its restructuring plan is much less costly than expected, has positively impacted the creditors of the banks in the sample by reducing contagion risk. This positive impact is reflected in the decreasing CDS spread changes at the individual bank level. However, since event 12 is associated with reduced regulatory intensity, the values are multiplied by −1, leading to positive abnormal CDS spread changes.

The U.S. CDS market reaction is generally negative but insignificant. While stock market reactions differ, CDS responses are similar in both regions, likely because CDS portfolios are dominated by large banks with similar market risk frameworks. From a creditor's perspective, the lack of reaction may stem from the balancing effects of risk reduction and diminished bailout expectations. The U.S. response may also be linked to the Volcker Rule, as Schäfer et al. (2016) show increased CDS spreads following its introduction, implying that additional BCBS regulations have a relatively limited impact.

Table 3: Market Reactions to Announcements Regarding Market Risk Regulation

	$\sum \overline{CMAR}_{m\_ew}$	$\sum \overline{CAR}_{m\_ew}$	$\sum \overline{CMAR}_{m\_mw}$	$\sum \overline{CAR}_{m\_mw}$
Panel A: EU				
Actual Events				
Sum (all events)	−0.1476**	−0.1182*	−0.2016**	−0.1693**
p value (all events)	0.025	0.077	0.012	0.028
Sum (market-only events)	-0.0532	-0.0303	-0.0352	-0.0012
p value (market-only events)	0.372	0.585	0.595	0.986
Placebo Events				
Sum (all events)	-0.0219	-0.0034	0.0086	0.0417
p value (all events)	0.763	0.959	0.911	0.582
Sum (market-only events)	-0.0613	-0.0340	-0.0605	-0.0329
p value (market-only events)	0.298	0.537	0.366	0.602
Panel B: U.S.				
Actual Events				
Sum (all events)	0.0671	0.0733	-0.0358	-0.0711
p value (all events)	0.261	0.236	0.719	0.469
Sum (market-only events)	0.0526	0.0688	0.0741	0.0616

p value (market-only events)	0.263	0.151	0.269	0.344
Placebo Events				
Sum (all events)	0.0044	0.0318	0.0339	0.0672
p value (all events)	0.955	0.625	0.731	0.495
Sum (market-only events)	0.0268	0.0464	0.1029	0.0905
p value (market-only events)	0.567	0.330	0.138	0.177

	$\sum \overline{\Delta CMAS}_{m\_ew}$	$\sum \overline{\Delta CAS}_{m\_ew}$	$\sum \overline{\Delta CMAS}_{m\_mw}$	$\sum \overline{\Delta CAS}_{m\_mw}$
Panel A: EU				
Actual Events				
Sum (all events)	0.0029	-0.0444	-0.0133	-0.0106
p value (all events)	0.984	0.797	0.948	0.951
Sum (market-only events)	-0.1437	-0.1792	-0.197	-0.1973
p value (market-only events)	0.292	0.243	0.188	0.249
Placebo Events				
Sum (all events)	0.4644***	0.4149**	0.5742***	0.5635***
p value (all events)	0.002	0.024	0.000	0.003
Sum (market-only events)	0.3478**	0.3126*	0.4277***	0.4018**
p value (market-only events)	0.016	0.051	0.004	0.025
Panel B: U.S.				
Actual Events				
Sum (all events)	-0.1224	-0.1593	-0.1353	-0.2006
p value (all events)	0.513	0.433	0.493	0.376
Sum (market-only events)	-0.0693	-0.1117	-0.0892	-0.1395
p value (market-only events)	0.607	0.466	0.541	0.409
Placebo Events				
Sum (all events)	0.3013	0.2453	0.3401	0.2993
p value (all events)	0.134	0.236	0.107	0.183
Sum (market-only events)	0.1468	0.0348	0.1557	0.0364
p value (market-only events)	0.337	0.824	0.324	0.830

This table presents aggregated EU and U.S. stock and CDS market reactions to 15 regulatory announcements of market risk by the BCBS. $CAR_{i,t}$, $CMAR_{i,t}$, $\Delta CAS_{i,t}$, and $\Delta CMAS_{i,t}$ are calculated according to Eq. (3)–Eq. (10). The MSCI World index is employed as a proxy for the stock market portfolio. The iTraxx Europe 5-years and iTraxx CDX IG 5-years indices are selected as proxies for the EU and U.S. CDS market portfolios, respectively. For each of the 15 market events (m), the average values $\overline{CAR}_m$, $\overline{CMAR}_m$, $\overline{\Delta CAS}_m$, $\overline{\Delta CMAS}_m$ are computed based on equally weighted (ew) and market-weighted (mw) portfolios. These values are multiplied by -1 if the event is associated with a reduction in regulatory intensity. The stock market reaction is reported as the sum of cumulative average abnormal returns $\sum \overline{CAR}_m$ and the sum of cumulative average market-adjusted returns $\sum \overline{CMAR}_m$ over 15 events. The CDS market reaction is reported as the sum of cumulative average abnormal CDS spread changes $\sum \overline{\Delta CAS}_m$ and the sum of cumulative average market-adjusted CDS spread changes $\sum \overline{\Delta CMAS}_m$ over 15 events. In addition, aggregated market reactions are calculated for market-only events; i.e., four market events that are announced simultaneously with credit and liquidity events are excluded (events 3, 4, 8, and 13). Abnormal stock and CDS market reactions are computed for placebo events five trading days prior to the actual events to assess potential information leakage and market anticipation. All values are tested for significance using a block bootstrap significance test (see Sec. 2.5.3). Computed p values are based on a two-sided significance test: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

The cross-sectional results show that a bank's capitalization has no effect on stock market reactions in the EU or U.S. However, a higher TIER1_RAT significantly reduces CDS spreads in both regions. This finding implies that better-capitalized banks are viewed as less risky by creditors, which is in line with $H1_{U.S.,EU,m}$.

A bank's market risk, tested in $H2_{U.S.,EU,m}$, is proxied in the EU by the ratio of marketable securities to total assets (SEC_ASSET). One coefficient for the stock market reaction is negative and significant at the 5% level. However, two coefficients become significant at the 1% and 5% levels when the MSCI Europe index is used, supporting H2, as higher market risk for EU banks negatively impacts stock market reactions. The lack of significant coefficients for the market-only event estimates aligns with the findings for aggregated market-only reactions, which are insignificant due to the exclusion of key events 3 and 4. In contrast, the EU CDS market is generally unaffected by SEC_ASSET. The ratio of derivatives to total assets (DER_ASSET) serves as a proxy in the U.S. sample. The coefficient remains insignificant across all stock market estimates, aligning with the insignificant aggregated U.S. market reactions. The U.S. CDS market reactions, however, are positively influenced, with both coefficients for all market events being significant at the 1% level. This finding supports H2, meaning that banks with higher market risk are perceived as riskier by creditors. Compared with stock estimates, the significant impact on CDS can be attributed to the fact that the CDS portfolio consists exclusively of large banks, which are more likely to hold derivatives.[36] The insignificance of the market-only events can be related to the importance of the excluded events 3 and 4.

$H3_{U.S.,EU,m}$ examines the classification of a bank as a G-SIB. For EU banks, the coefficient is insignificant across all estimates for both stock and CDS markets. The results of the U.S. regressions, however, align with the expected mechanism. There is a negative effect on stock market reactions, which is significant at the 1% and 5% levels for all market events, and a positive effect on the CDS market, which is significant at the 5% level for all market events (estimate (5)) and at the 1% level for market-only events. In the U.S., classification as a G-SIB reflects higher trading activity.

Regarding the EU, the feedback loop discussed in $H4_{EU,m}$ proves irrelevant for shareholders and creditors, as all the coefficients of GIIPS∗SOV_DEBT are insignificant. This irrelevance may stem from the mechanism's focus on credit risk and funding conditions, making its role in market risk negligible. However, the coefficients of GIIPS are negative and highly significant in the stock market estimates but can only be interpreted as conditional on SOV_DEBT=0 due to the interaction term. To assess the overall GIIPS impact, the regressions are re-estimated without the interaction term. The coefficients in all estimations are negative and significant at the 1% level, suggesting that GIIPS banks in particular drive the negative stock market reaction.[37]

[36] Descriptive statistics in C show that there is a high dispersion of the variable DER_ASSET because certain large banks (e.g., Morgan Stanley, Goldman Sachs) hold a multiple of derivatives to total assets. Unreported analyses expectedly show a significantly higher level of DER_ASSET for banks in the U.S. CDS portfolio.

[37] The results are available upon request.

Table 4: Determinants of Stock and CDS Market Reactions to Market Risk Regulation

	Stock Market				CDS Market			
	Market Events		Market-Only		Market Events		Market-Only	
	CAR	CMAR	CAR	CMAR	ΔCAS	$\Delta CMAS$	ΔCAS	$\Delta CMAS$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: EU								
TIER1_RAT	−0.019	0.059	−0.160	0.076	−0.654**	−0.381	−0.932***	−0.646*
	(0.129)	(0.124)	(0.163)	(0.136)	(0.264)	(0.269)	(0.327)	(0.362)
TIER1_RAT^2	0.075	−0.114	0.512	−0.138				
	(0.248)	(0.259)	(0.428)	(0.373)				
SEC_ASSET	−0.041**	−0.028	−0.009	0.007	−0.018	−0.010	0.037	0.075
	(0.018)	(0.018)	(0.017)	(0.017)	(0.049)	(0.064)	(0.054)	(0.073)
G_SIB	0.003	0.003	0.004	0.007	0.010	−0.015	0.007	−0.022
	(0.013)	(0.011)	(0.006)	(0.006)	(0.032)	(0.020)	(0.040)	(0.024)
GIIPS	−0.014**	−0.015***	−0.025***	−0.022***	−0.011	−0.005	−0.029	−0.015
	(0.006)	(0.006)	(0.005)	(0.005)	(0.019)	(0.018)	(0.023)	(0.020)
SOV_DEBT	0.003	−0.006	0.001	−0.008*	0.020**	0.001	0.006	−0.012
	(0.005)	(0.005)	(0.004)	(0.005)	(0.009)	(0.014)	(0.013)	(0.017)
GIIPS∗SOV_DEBT	−0.009	−0.007	0.002	0.001	−0.011	−0.006	−0.004	0.001
	(0.007)	(0.007)	(0.007)	(0.007)	(0.012)	(0.019)	(0.014)	(0.019)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	826	826	565	565	268	268	183	183
R^2	0.059	0.061	0.025	0.031	0.257	0.187	0.131	0.055
Panel B: U.S.								
TIER1_RAT	−0.061	−0.067	0.015	0.005	−1.158***	−0.203	−1.055***	0.215
	(0.065)	(0.062)	(0.067)	(0.063)	(0.232)	(0.193)	(0.377)	(0.346)
TIER1_RAT^2	0.091	0.120	−0.071	−0.052				
	(0.163)	(0.155)	(0.164)	(0.149)				
DER_ASSET	0.0002	0.0002	0.00002	−0.00005	0.001***	0.0005***	0.0003	−0.0002
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.0002)	(0.0004)	(0.0004)
G_SIB	−0.013***	−0.011**	−0.004	−0.001	0.110**	0.041	0.224***	0.110***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.056)	(0.032)	(0.045)	(0.034)

Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2,919	2,919	1,985	1,985	116	116	77	77
R^2	0.043	0.026	0.053	0.062	0.601	0.420	0.424	0.326

This table presents the variables explaining heterogeneous reactions in the dependent variable, defined as either $CAR_{i,t}$, $CMAR_{i,t}$, $\Delta CAS_{i,t}$, or $\Delta CMAS_{i,t}$, across 15 market events announced by the BCBS, for EU and U.S. banks. These values are calculated according to Eq. (3)–Eq. (10). Dependent variables are multiplied by -1 if the event is associated with a reduction in regulatory intensity. The MSCI World index is used as proxy for the stock market portfolio. The iTraxx Europe 5-years and the iTraxx CDX IG 5-years indices are used as proxies for the EU and U.S. CDS market portfolios, respectively. For so-called market-only events, market events are excluded (events 3, 4, 8, 13) if they are announced simultaneously with credit and liquidity events. The bank-specific variables are TIER1_RAT, SEC_ASSET, DER_ASSET and G_SIB. TIER1_RAT is the ratio of Tier 1 capital to total risk-weighted assets. SEC_ASSET is the ratio of marketable security investments to total assets. DER_ASSET is ratio of derivatives to total assets. G_SIB is a dummy variable that is 1 for G-SIBs and 0 otherwise. The country-specific variable is GIIPS. GIIPS is a dummy variable that is 1 for EU banks located in Greece, Italy, Ireland, Portugal or Spain and 0 otherwise. SOV_DEBT is a dummy variable that is 1 for the sovereign debt crisis (2010-05-02–2013-06-30) and 0 otherwise. The control variables are SIZE, COST_INC, ROA and dummies for the subprime crisis (2007-06-01–2008-09-14) and the GFC (2008-09-15–2010-05-01) for EU portfolios, while U.S. portfolios also include the sovereign debt crisis dummy. SIZE is the natural logarithm of total assets. COST_INC is the cost-to-income ratio. ROA is the return on assets. Regressions are estimated using random effects with clustered standard errors at bank level reported in parentheses. Computed p values are based on a two-sided significance test: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

2.6.2 Credit Risk

The EU stock market reaction is clearly negative. For the equally weighted portfolio, the overall effects are -0.2335 ($\sum \overline{CMAR}_{c\_ew}$) and -0.2008 ($\sum \overline{CAR}_{c\_ew}$), significant at the 1% and 5% levels, respectively. The market-weighted portfolio shows a stronger negative impact of -0.4091 ($\sum \overline{CMAR}_{c\_mw}$) and -0.3491 ($\sum \overline{CAR}_{c\_mw}$), with both values significant at the 1% level. Excluding credit events announced with liquidity and market events—events 2, 3, 5, 7, 9, 19, 20, and 25—leaves 18 credit-only events. The credit-only analysis confirms the initial results, with $\sum \overline{CMAR}_{c\_mw}$ at -0.1595 significant at the 10% level. The results are more pronounced with the MSCI Europe index as the stock market proxy, where both market-weighted responses (-0.1717 $\sum \overline{CMAR}_{c\_mw}$, -0.1449 $\sum \overline{CAR}_{c\_mw}$) are significant at the 5% level. Overall, this indicates a decline in shareholder value for EU banks, especially larger banks.

The U.S. reaction follows a similar trend but is less pronounced. While equally weighted responses are insignificant, market-weighted portfolios show clearer effects, with -0.2560 ($\sum \overline{CMAR}_{c\_mw}$) and -0.2741 ($\sum \overline{CAR}_{c\_mw}$), significant at the 10% and 5% levels, respectively. The credit-only analysis confirms consistent negative results, though none are significant. While shareholders of larger banks appear to experience significant wealth loss, all credit-only events are insignificant. The influence of the eight excluded credit events (2, 3, 5, 7, 9, 19, 20, and 25) is therefore examined, revealing that only $\sum \overline{CAR}_{c\_mw}$, with a value of -0.1757, is significant at the 5% level when the MSCI USA index is used for calculation. Given the insignificance of credit-only events and limited significance of excluded events, the case for a significantly negative U.S. stock market reaction is weak.

Similar to market risk, the responses of U.S. and EU stock markets differ, reflecting divergent implementation of regulations and the structure of their banking systems. In the EU, the uniform implementation across banks results in consistently negative reactions for both equally and market-weighted portfolios, with the effect being more pronounced for the latter. In the U.S., the variation in effect size and significance suggests a limited impact on smaller banks. This may be due, in part, to Basel II applying only to large banks, so that expectations for a similar implementation arise for Basel III. Furthermore, the Basel III credit risk framework was adjusted by U.S. agencies so that certain rules apply only to banks with total assets of ≥ $250 billion, and SBHCs are entirely exempt. The changes to credit risk under Basel IV shall also apply only to large banks in Categories I-IV.

Creditors of EU banks react with an increased risk perception. Positive abnormal CDS spread changes of 0.2501 ($\sum \overline{\Delta CMAS}_{c\_ew}$), 0.3519 ($\sum \overline{\Delta CAS}_{c\_ew}$), 0.3194 ($\sum \overline{\Delta CMAS}_{c\_mw}$), and 0.4033 ($\sum \overline{\Delta CAS}_{c\_mw}$) are observed. The third value is significant at the 10% level, whereby the second and last values are significant at the 5% level. The credit-only analysis supports the direction of the effect, but the effect size is reduced, with no significant values. To further analyze market reactions, the CDS market response for the eight omitted events (events 2, 3, 5, 7, 9, 19, 20 and 25) is calculated. These lead to positive reactions of 0.2483 $\sum \overline{\Delta CMAS}_{c\_ew}$, 0.2587 $\sum \overline{\Delta CAS}_{c\_ew}$, 0.2917 $\sum \overline{\Delta CMAS}_{c\_mw}$, and 0.3006 $\sum \overline{\Delta CAS}_{c\_mw}$, all significant at the 5% level. These events explain much of the market reaction, which clarifies why the credit-only events lack significance. While these credit events coincide with market and liquidity regulation, EU CDS markets show no significant response to such regulations, suggesting the observed effects are due to credit regulation. Creditors respond with increasing CDS spreads, as they perceive a reduced likelihood of a bailout. All four values of the U.S. CDS market reaction are positive and even larger than those of the EU, though none are statistically significant. Similar to market risk, the Dodd-Frank Act can be cited as an explanation for the lack of significance. In addition to the Volcker Rule, Schäfer et al. (2016) provide evidence of increased CDS spreads due to the Dodd-Frank Act. They attribute this rise to reduced bailout expectations, driven by enhanced prudential regulation and improved resolution procedures.[38] Additionally, the non-bailout of Lehman Brothers in 2008 may have already diminished expectations for future bailouts.

Table 5: Market Reactions to Announcements Regarding Credit Risk Regulation

	$\sum \overline{CMAR}_{c\_ew}$	$\sum \overline{CAR}_{c\_ew}$	$\sum \overline{CMAR}_{c\_mw}$	$\sum \overline{CAR}_{c\_mw}$
Panel A: EU				
Actual Events				
Sum (all events)	-0.2335^{***}	-0.2008^{**}	-0.4091^{***}	-0.3491^{***}
p value (all events)	0.007	0.019	0.000	0.001
Sum (credit-only events)	-0.0804	-0.0676	-0.1595^{*}	-0.1225

[38] See Title II–Orderly Liquidation Authority of the Dodd-Frank Act for measures designed to prevent bailouts.

p value (credit-only events)	0.268	0.354	0.075	0.137
Placebo Events				
Sum (all events)	0.0663	0.0560	0.0675	0.0361
p value (all events)	0.450	0.538	0.531	0.727
Sum (credit-only events)	0.0460	0.0294	0.0096	-0.0401
p value (credit-only events)	0.535	0.680	0.911	0.598
Panel B: U.S.				
Actual Events				
Sum (all events)	-0.0353	-0.0705	-0.2560^{*}	-0.2741^{**}
p value (all events)	0.632	0.368	0.087	0.047
Sum (credit-only events)	-0.0404	-0.0708	-0.1402	-0.1439
p value (credit-only events)	0.521	0.222	0.153	0.132
Placebo Events				
Sum (all events)	0.0405	0.0773	-0.0152	0.0252
p value (all events)	0.587	0.320	0.909	0.870
Sum (credit-only events)	0.0019	0.0250	-0.0340	-0.0489
p value (credit-only events)	0.976	0.693	0.702	0.581

	$\sum \overline{\Delta CMAS}_{c\_ew}$	$\sum \overline{\Delta CAS}_{c\_ew}$	$\sum \overline{\Delta CMAS}_{c\_mw}$	$\sum \overline{\Delta CAS}_{c\_mw}$
Panel A: EU				
Actual Events				
Sum (all events)	0.2501	0.3519^{**}	0.3194^{*}	0.4033^{**}
p value (all events)	0.120	0.043	0.067	0.048
Sum (credit-only events)	0.0019	0.0932	0.0277	0.1028
p value (credit-only events)	0.986	0.493	0.838	0.513
Placebo Events				
Sum (all events)	0.1890	0.2097	0.1661	0.1897
p value (all events)	0.249	0.238	0.348	0.349
Sum (credit-only events)	0.1547	0.0679	0.1475	0.0702
p value (credit-only events)	0.207	0.621	0.294	0.644
Panel B: U.S.				
Actual Events				
Sum (all events)	0.2814	0.3706	0.3473	0.4164
p value (all events)	0.267	0.202	0.191	0.184
Sum (credit-only events)	0.1525	0.1999	0.1847	0.2289
p value (credit-only events)	0.408	0.369	0.350	0.319
Placebo Events				
Sum (all events)	0.2383	0.4041	0.3504	0.5002
p value (all events)	0.328	0.160	0.188	0.101
Sum (credit-only events)	0.2205	0.2685	0.2779	0.3301
p value (credit-only events)	0.249	0.227	0.169	0.159

This table presents aggregated EU and U.S. stock and CDS market reactions to 26 regulatory announcements of credit risk by the BCBS. $CAR_{i,t}$, $CMAR_{i,t}$, $\Delta CAS_{i,t}$, and $\Delta CMAS_{i,t}$ are calculated according to Eq. (3)–Eq. (10). The MSCI World index is selected as a proxy for the stock market portfolio. The iTraxx Europe 5-years and iTraxx CDX IG 5-years indices are employed as proxies for the EU and U.S. CDS market portfolios, respectively. For each of the 26 credit events (c), average values $\overline{CAR_c}$, $\overline{CMAR_c}$, $\overline{\Delta CAS_c}$, $\overline{\Delta CMAS_c}$ are computed based on equally weighted (ew) and market-weighted (mw) portfolios. These values are multiplied by -1 if the event is associated with a reduction in regulatory intensity. The stock market reaction is reported as the sum of cumulative average abnormal returns $\sum \overline{CAR_c}$ and the sum of cumulative average market-adjusted returns $\sum \overline{CMAR_c}$ over 26 events. The CDS market reaction is reported as the sum of cumulative average abnormal CDS spread changes $\sum \overline{\Delta CAS_c}$ and the sum of cumulative average market-adjusted CDS spread changes $\sum \overline{\Delta CMAS_c}$ over 26 events. In addition, aggregated market reactions are calculated for credit-only events; i.e., eight credit events that are announced simultaneously with market and liquidity events are excluded (events 2, 3, 5, 7, 9, 19, 20, and 25). Abnormal stock and CDS market reactions are computed for placebo events five trading days prior to the actual events to assess potential information leakage and market anticipation. All values are tested for significance using a block bootstrap significance test (see Sec. 2.5.3). Computed p values are based on a two-sided significance test: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

The first hypothesis focuses on bank capitalization. For U.S. banks, the expected positive but diminishing effect of TIER1_RAT on stock market reactions is clear. Three coefficients are significant at the 5% level and one is significant at the 10% level, which holds for the squared term's coefficients. The initially positive impact is attributed to greater regulatory compliance. However, beyond a certain threshold, the capital costs outweigh these benefits, with turnaround values of around 20%. Interestingly, this mechanism cannot be observed among EU shareholders, and the lack of response cannot be attributed to large differences in TIER1_RAT levels across jurisdictions (see C). An explanation for the U.S. effect is that only the advanced Basel II approaches were mandatory only for large banks (e.g. 17 banks in 2011), meaning the majority of U.S. banks remained regulated under Basel I. Moreover, even banks subject to Basel II continued reporting capital ratios according to Basel I during the parallel run (Basel Committee on Banking Supervision, 2012). In contrast, Basel II was mandatory for EU banks, helping them become familiar with the regulatory framework and better understand the implications of Basel III. This prior experience allowed them to be more prepared in advance, potentially leading to more consistent effects from the new regulation. Meanwhile, the uncertainty surrounding actual capital requirements for U.S. banks that were newly regulated under Basel III may have reassured shareholders of banks with higher capital reserves. Regarding the U.S. CDS market, no effect can be demonstrated. The influence on EU creditors is initially ambiguous, because the coefficient in estimation (5) is negative and significant at the 1% level for all credit events, whereas the coefficient in estimation (8) is positive and significant at the 5% level for credit-only events. To further investigate this, the regressions where the endogenous variable was calculated using the single-index model are considered. This analysis reveals a negative coefficient that is significant at the 10% level. Overall, there is at least some support for a negative influence of TIER1_RAT on the EU CDS market reaction.

According to $H2_{U.S.,EU,c}$, bank's credit risk is modeled as the ratio of total loans to total assets (LOAN_ASSET). There is no impact for either the EU or U.S. shareholders and creditors. This suggests that the credit risk itself does not explain variations in market responses. Consistent with $H3_{U.S.,EU,c}$, the costs of credit risk are approximated with provisions for loan loss to total loans (PROV_LOAN). For the EU stock market, there is no impact. One coefficient in the U.S. stock market estimates for credit-only events is negative and significant at the 10% level. This finding holds for the credit-only estimates where the dependent variable is calculated using the MSCI USA, with coefficients being significant at the 5% and 10% levels, respectively. The negative impact of higher risk costs in the U.S. can again be explained by the regulatory changes affecting large parts of the U.S. banking landscape as a result of Basel III. PROV_LOAN has a negative effect on EU CDS spreads, with the coefficient in estimate (7) for credit-only events being significant at the 5% level. In the estimates where the endogenous variable is calculated with the single-index model, the coefficients are also negative and significant at the 10% and 5% levels, respectively. In contrast, the coefficients in all four estimates of the U.S. CDS market reaction are consistently positive and significant. This opposing effect is likely due to differences in accounting standards. Banks in the EU CDS portfolio adhere to International Financial Reporting Standards (IFRS), while those in the U.S. sample follow United States Generally Accepted Accounting Principles (US-GAAP). Under US-GAAP, loan write-downs are strictly based on incurred losses, whereas IFRS allows for a more forward-looking approach to risk assessment. Creditors of EU banks reward a more precise and cautious risk assessment, while loan write-downs at U.S. banks come as a negative surprise. The classification of a bank as a G-SIB discussed in $H4_{U.S.,EU,c}$ does not explain stock or CDS market reactions in either the EU or the U.S. Regarding the jurisdictional hypotheses, there is a highly significant and positive effect of the feedback loop on shareholders, with all four coefficients in the estimates being significant at the 1% level. In contrast, the CDS market estimates show negative and significant coefficients for estimates (5) and (7) at the 5% and 10% levels. This contradicts the hypothesized mechanism of $H5_{EU,c}$. Besides creditors, shareholders of GIIPS banks may view regulation as desirable if it helps contain the excessive risks associated with these banks. With regard to $H5_{U.S.,c}$ and the distinction between SBHCs and institutions affected by the U.S. credit risk framework in general, there is a negative effect in line with the hypothesis. The coefficient of AFF_BANK_c in estimates (2) and (4) is at the 1% and 10% level significant, respectively. Both coefficients are significant at the 1% level in the estimations where the market reaction is calculated with the MSCI USA index.

Table 6: Determinants of Stock and CDS Market Reactions to Credit Risk Regulation

	Stock Market				CDS Market			
	Credit Events		Credit-Only		Credit Events		Credit-Only	
	CAR	CMAR	CAR	CMAR	ΔCAS	$\Delta CMAS$	ΔCAS	$\Delta CMAS$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: EU								
TIER1_RAT	−0.010	0.006	−0.129	−0.106	−0.329***	−0.001	−0.103	0.225**
	(0.092)	(0.085)	(0.104)	(0.092)	(0.087)	(0.095)	(0.084)	(0.103)
TIER1_RAT^2	−0.092	−0.119	0.154	0.056				
	(0.257)	(0.235)	(0.281)	(0.294)				

LOAN_ASSET	−0.022	−0.016	−0.024	−0.032	0.044*	0.011	−0.002	−0.022
	(0.016)	(0.014)	(0.019)	(0.022)	(0.023)	(0.025)	(0.023)	(0.027)
PROV_LOAN	0.107	0.046	−0.021	−0.041	−0.533	−0.017	−0.941**	−0.028
	(0.151)	(0.158)	(0.160)	(0.208)	(0.362)	(0.314)	(0.379)	(0.324)
G_SIB	−0.009	−0.009	−0.008	−0.010	0.005	−0.001	−0.004	−0.007
	(0.007)	(0.007)	(0.007)	(0.009)	(0.014)	(0.011)	(0.007)	(0.007)
GIIPS	−0.008*	−0.012**	−0.009	−0.011*	0.008	0.020**	0.017**	0.023**
	(0.004)	(0.004)	(0.006)	(0.007)	(0.009)	(0.009)	(0.008)	(0.009)
SOV_DEBT	−0.005**	−0.008***	−0.004*	−0.006***	0.019***	0.024***	0.017**	0.025***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.005)	(0.007)	(0.005)
GIIPS∗SOV_DEBT	0.014***	0.015***	0.020***	0.020***	−0.022**	−0.011	−0.017*	−0.009
	(0.005)	(0.005)	(0.007)	(0.007)	(0.009)	(0.008)	(0.009)	(0.009)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,510	1,510	1,067	1,067	632	632	444	444
R^2	0.018	0.014	0.018	0.012	0.112	0.101	0.097	0.065
Panel B: U.S.								
TIER1_RAT	0.128**	0.115**	0.102*	0.115**	0.082	0.301	0.365	0.268
	(0.050)	(0.046)	(0.053)	(0.054)	(0.254)	(0.259)	(0.319)	(0.283)
TIER1_RAT^2	−0.303**	−0.270**	−0.244*	−0.290**				
	(0.127)	(0.111)	(0.138)	(0.138)				
LOAN_ASSET	−0.004	−0.004	−0.002	−0.003	−0.058	−0.018	0.025	−0.028
	(0.006)	(0.004)	(0.008)	(0.008)	(0.092)	(0.035)	(0.069)	(0.048)
PROV_LOAN	−0.002	−0.010	−0.214*	−0.126	0.942**	0.414*	1.037***	0.578**
	(0.085)	(0.076)	(0.117)	(0.121)	(0.367)	(0.250)	(0.326)	(0.240)
G_SIB	−0.007**	−0.004	0.001	0.004	0.065	0.004	0.056	−0.024
	(0.004)	(0.003)	(0.004)	(0.004)	(0.047)	(0.018)	(0.039)	(0.022)
AFF_BANK_c	−0.002	−0.005***	0.002	−0.003*				
	(0.002)	(0.002)	(0.002)	(0.002)				
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	5,388	5,388	3,732	3,732	207	207	143	143
R^2	0.032	0.021	0.131	0.076	0.171	0.093	0.159	0.135

This table presents the variables explaining heterogeneous reactions in the dependent variable, defined as either $CAR_{i,t}$,

$CMAR_{i,t}$, $\Delta CAS_{i,t}$, or $\Delta CMAS_{i,t}$, across 26 credit events announced by the BCBS, for EU and U.S. banks. These values are calculated according to Eq. (3)–Eq. (10). Dependent variables are multiplied by -1 if the event is associated with a reduction in regulatory intensity. The MSCI World index is used as proxy for the stock market portfolio. The iTraxx Europe 5-years and the iTraxx CDX IG 5-years indices are used as proxies for the EU and U.S. CDS market portfolios, respectively. For so-called credit-only events, credit events are excluded (events 2, 3, 5, 7, 9, 19, 20, 25) if they are announced simultaneously with market and liquidity events. The bank-specific variables are TIER1_RAT, LOAN_ASSET, PROV_LOAN and G_SIB. TIER1_RAT is the ratio of Tier 1 capital to total risk-weighted assets. LOAN_ASSET is the ratio of total loans to total assets. PROV_LOAN is the ratio of loan-loss provisions to total loans. G_SIB is a dummy variable that is 1 for G-SIBs and 0 otherwise. The country-specific variables are GIIPS and AFF_BANK_c. GIIPS is a dummy variable that is 1 for EU banks located in Greece, Italy, Ireland, Portugal or Spain and 0 otherwise. AFF_BANK_c is a dummy variable that is 1 for U.S. banks that are not subject to the Board's SBHC Policy Statement and 0 otherwise. SOV_DEBT is a dummy variable that is 1 for the sovereign debt crisis (2010-05-02–2013-06-30) and 0 otherwise. The control variables are SIZE, COST_INC, ROA and a dummy for the GFC (2008-09-15–2010-05-01) for EU portfolios, while U.S. portfolios also include the sovereign debt crisis dummy. SIZE is the natural logarithm of total assets. COST_INC is the cost-to-income ratio. ROA is the return on assets. Regressions are estimated using random effects with clustered standard errors at bank level reported in parentheses. Computed p values are based on a two-sided significance test: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

2.6.3 Liquidity Risk

Regarding liquidity regulation, both the EU stock market (-0.0659 $\sum \overline{CMAR}_{l\_ew}$, -0.0301 $\sum \overline{CAR}_{l\_ew}$, -0.0858 $\sum \overline{CMAR}_{l\_mw}$, -0.0471 $\sum \overline{CAR}_{l\_mw}$) and U.S. stock market (0.0236 $\sum \overline{CMAR}_{l\_ew}$, 0.0279 $\sum \overline{CAR}_{l\_ew}$, 0.0801 $\sum \overline{CMAR}_{l\_mw}$, 0.0944 $\sum \overline{CAR}_{l\_mw}$) show no significant reaction, which holds for liquidity-only events (events 4, 5, 6 and 11 are removed). While the EU reaction is negative, the U.S. reaction is positive. The EU stock market reaction is not significant, but its direction aligns with the findings of Bruno et al. (2018). Although their study includes only seven events due to the timing of publication, the inclusion of six additional events in this analysis confirms the consistency of the effect's direction. This finding suggests that the following six events can be considered noise, which is explained by the fact that a habituation effect occurs in the market, causing the informational impact of regulatory events to decrease over time. The difference in sign between EU and U.S. reactions may be explained by the less strict U.S. implementation (it applies only to large banks) and their comparatively better liquidity position. Most U.S. banks in the sample are not subject to these regulations, and the institutions that are covered face less pressure to restructure their assets and funding to comply with the new rules.

Analogous to the stock market, the creditors of EU banks exhibit an insignificant response. The observed reactions are positive and as follows: 0.2106 $\sum \overline{\Delta CMAS}_{l\_ew}$, 0.1080 $\sum \overline{\Delta CAS}_{l\_ew}$, 0.1289 $\sum \overline{\Delta CMAS}_{l\_mw}$, and 0.0283 $\sum \overline{\Delta CAS}_{l\_mw}$. Similar to the findings of Simion et al. (2024), CDS spreads have risen, though unlike their results, no significance was found. Several factors may explain this. On the one hand, there are methodological differences, as this paper calculates the aggregated overall effect and uses a bootstrap simulation to calculate significance. This requires the use of a balanced panel to sum the average abnormal market reactions, significantly reducing the sample size. Additionally, due to the focus on EU banks, Swiss banks are not included in the analysis. Notably, significance is evident only for the (0,0) window in the study of Simion et al.

(2024), and their result for the (-1;+1) window is similar to the findings in this paper.

The U.S. CDS market displays a markedly positive and significant response, reflecting heightened perceived credit risk: 0.4532 ($\sum \overline{\Delta CMAS}_{l\_ew}$), 0.3444 ($\sum \overline{\Delta CAS}_{l\_ew}$), 0.1311 ($\sum \overline{\Delta CMAS}_{l\_mw}$), and 0.1132 ($\sum \overline{\Delta CAS}_{l\_mw}$). Among these, the first and last values are significant at the 5% level, while the third is significant at the 1% level. A similar pattern emerges when analyzing liquidity-only events, though significance is found only in $\sum \overline{\Delta CMAS}_{l\_mw}$, which records a value of 0.0878, significant at the 5% level. The analysis of individual events shows that the rise in U.S. CDS spreads is mainly driven by events 3 and 4. Event 3, following the Lehman Brothers collapse, saw hedge funds withdraw nearly one-third of their assets from Morgan Stanley, as reported by the Financial Times on September 25, 2008. Shortly after, on September 29, 2008, Morgan Stanley received a $9 billion investment from Mitsubishi UFJ, and news broke of Citigroup's takeover of Wachovia. Though not an official event date, these factors likely influenced the reaction of the U.S. stock market. Morgan Stanley's CDS spread increases were notably high at 0.8162 ΔCAS and 0.8755 $\Delta CMAS$, creating a significant bias in event 3 as the effect is averaged over only eight banks. During event 4 on December 17, 2009, Morgan Stanley announced a $2.2 billion quarterly loss, further boosting CDS spreads. Therefore, the positive U.S. reactions are not attributable to liquidity risk regulation itself. Rules are comparable for EU and U.S. banks, as the U.S. portfolio includes only large banks, making the LCR and NSFR binding. Both portfolios show rising CDS spreads, but the larger effect and significance in the U.S. portfolio is due to confounding events. The results of the cross-sectional analysis for U.S. CDSs are therefore not presented, as confounding events drive the reaction.

Table 7: Market Reactions to Announcements Regarding Liquidity Risk Regulation

	$\sum \overline{CMAR}_{l\_ew}$	$\sum \overline{CAR}_{l\_ew}$	$\sum \overline{CMAR}_{l\_mw}$	$\sum \overline{CAR}_{l\_mw}$
Panel A: EU				
Actual Events				
Sum (all events)	-0.0659	-0.0301	-0.0858	-0.0471
p value (all events)	0.314	0.610	0.283	0.510
Sum (liquidity-only events)	-0.0085	0.0076	0.0153	0.0174
p value (liquidity-only events)	0.896	0.897	0.830	0.789
Placebo Events				
Sum (all events)	-0.0658	-0.0583	-0.0306	-0.0504
p value (all events)	0.314	0.337	0.716	0.487
Sum (liquidity-only events)	-0.0677	-0.0600	-0.0439	-0.0540
p value (liquidity-only events)	0.238	0.280	0.500	0.391
Panel B: U.S.				
Actual Events				
Sum (all events)	0.0236	0.0279	0.0801	0.0944
p value (all events)	0.712	0.683	0.458	0.396

Sum (liquidity-only events)	-0.0025	-0.0016	0.0764	0.0675
p value (liquidity-only events)	0.962	0.986	0.374	0.425
Placebo Events				
Sum (all events)	0.0415	0.0547	0.1444	0.1030
p value (all events)	0.509	0.408	0.224	0.353
Sum (liquidity-only events)	0.0175	0.0190	0.0549	0.0122
p value (liquidity-only events)	0.722	0.732	0.516	0.903

	$\sum \overline{\Delta CMAS}_{l\_ew}$	$\sum \overline{\Delta CAS}_{l\_ew}$	$\sum \overline{\Delta CMAS}_{l\_mw}$	$\sum \overline{\Delta CAS}_{l\_mw}$
Panel A: EU				
Actual Events				
Sum (all events)	0.2106	0.1080	0.1289	0.0283
p value (all events)	0.178	0.575	0.441	0.890
Sum (liquidity-only events)	0.0735	-0.056	0.0002	-0.1047
p value (liquidity-only events)	0.576	0.726	1.000	0.538
Placebo Events				
Sum (all events)	0.1062	0.0540	0.0537	0.0243
p value (all events)	0.484	0.757	0.768	0.899
Sum (liquidity-only events)	0.0885	0.0138	0.0404	-0.0132
p value (liquidity-only events)	0.498	0.931	0.752	0.946
Panel B: U.S.				
Actual Events				
Sum (all events)	0.4532**	0.3444	0.1311***	0.1132**
p value (all events)	0.022	0.119	0.004	0.023
Sum (liquidity-only events)	0.2856	0.1198	0.0878**	0.0624
p value (liquidity-only events)	0.196	0.489	0.042	0.127
Placebo Events				
Sum (all events)	0.0853	-0.1173	-0.0261	-0.0625
p value (all events)	0.603	0.564	0.460	0.136
Sum (liquidity-only events)	0.1689	-0.0337	-0.0054	-0.0379
p value (liquidity-only events)	0.240	0.827	0.852	0.288

This table presents aggregated EU and U.S. stock and CDS market reactions to 13 regulatory announcements of liquidity risk by the BCBS. $CAR_{i,t}$, $CMAR_{i,t}$, $\Delta CAS_{i,t}$, and $\Delta CMAS_{i,t}$ are calculated according to Eq. (3)–Eq. (10). The MSCI World index is selected as a proxy for the stock market portfolio. The iTraxx Europe 5-years and iTraxx CDX IG 5-years indices are employed as proxies for the EU and U.S. CDS market portfolios, respectively. For each of the 13 liquidity events (l), average values $\overline{CAR}_l$, $\overline{CMAR}_l$, $\overline{\Delta CAS}_l$, $\overline{\Delta CMAS}_l$ are computed based on equally weighted (ew) and market-weighted (mw) portfolios. These values are multiplied by -1 if the event is associated with a reduction in regulatory intensity. The stock market reaction is reported as the sum of cumulative average abnormal returns $\sum \overline{CAR}_l$ and the sum of cumulative average market-adjusted returns $\sum \overline{CMAR}_l$ over 13 events. The CDS market reaction is reported as the sum of cumulative average abnormal CDS spread changes $\sum \overline{\Delta CAS}_l$ and the sum of cumulative average market-adjusted CDS spread changes $\sum \overline{\Delta CMAS}_l$ over 13 events. In addition, aggregated market reactions are calculated for liquidity-only events; i.e., four liquidity events that are announced simultaneously with market and credit events are excluded (events 4, 5, 6, and 11). Abnormal stock and CDS market reactions are computed for placebo events five trading days prior to the actual events to assess potential information leakage and market anticipation. All values are tested for significance using a block bootstrap significance test (see Sec. 2.5.3). Computed p values are based on a two-sided significance test: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

In the first step, the determinants of the EU responses are discussed. The assumed influence of LCR_PROXY, according to $H1_{EU,l}$, is evident in the CDS market, as all coefficients are negative and significant at the 1% level. From a creditor's perspective, a more liquid balance sheet leads to greater resilience against liquidity shocks, which aligns with the findings of (Simion et al., 2024). Contrary to Bruno et al. (2018), no effect can be observed in the stock market, likely due to the decreasing relevance of the six additional events examined in this paper.

Regarding $H2_{EU,l}$, NSFR_PROXY negatively affects the stock market with the coefficients being significant at the 10% level for liquidity-only events. Contrary to the expectation, a lower funding mismatch (expressed by higher NSFR_PROXY) has a negative effect on a bank's stock market reaction, which is consistent with the results of Bruno et al. (2018). Analogously, pecking-order theory serves as an explanation (Myers and Majluf, 1984), because NSFR_PROXY contains equity, so capital costs increase as the funding mismatch decreases. Because well-capitalized banks with a lower funding mismatch face lower liquidity risk anyway, they may be less willing to bear the additional costs of adjusting assets and liabilities (Bruno et al., 2018). The smaller effect size in comparison and the lower significance can again be attributed to the little relevance of the additional six events in this paper. The significant influence of NSFR_PROXY compared to LCR_PROXY may be due to the fact that compliance with the NSFR is more costly from a shareholder's perspective. For the CDS market, NSFR_PROXY has no explanatory power. This may be due to the fact that cost considerations of pecking-order theory are less relevant from a creditor's perspective than the resilience against liquidity shocks, which can directly lead to insolvency.

The charter value of a bank explained in $H3_{EU,l}$ and proxied by DEP_ASSET, shows no effect on stock markets, while two coefficients in the CDS market estimations are significant at the 10% level. However, the coefficient in estimation (5) is negative, whereas in estimation (8) it is positive. To verify these findings, additionally the regressions are considered where the dependent variable is calculated with the single-index model. In this case, the coefficient is negative and significant at the 5% level in the regression that includes all liquidity events, providing some support for $H3_{EU,l}$ by suggesting that higher liquidity preserves a bank's charter value, thereby reducing CDS spreads.

Regarding the jurisdictional hypotheses, the assumed feedback loop effect, consistent with $H4_{EU,l}$, is evident. In the stock market estimates, all coefficients for GIIPS∗SOV_DEBT are negative and significant at the 1% level. In the CDS market, both coefficients are positive for liquidity-only events and significant at the 1% level. From a shareholder's perspective, the feedback loop increases compliance costs associated with liquidity ratios, while from a creditor's perspective, it heightens funding risk.

Regarding the U.S. determinants, the impact of the LCR and NSFR is analyzed for banks that must fully comply with the liquidity rules (FULL_AFF_l) and those that that are permitted to calculate modified metrics (MOD_AFF_l), while banks that are not affected constitute the reference category. The coefficients of the interaction terms of banks required to fully comply

FULL_AFF_l∗LCR_PROXY and FULL_AFF_l∗NSFR_PROXY are distinct negative and highly significant, both for all events and liquidity-only events. This is consistent with H1_B$_{U.S.,l,stock}$ and implies that the application of liquidity rules solely to large banks amounts to a one-sided sanction, thereby providing smaller banks with a competitive advantage. Regarding the interaction term with NSFR_PROXY, an additional argument again relates to the pecking-order theory. However, no significance is observed in the interactions of banks that are subject to the modified rules. The weakening of the liquidity rules for such banks also gives them a competitive advantage over the banks that must comply fully, which explains the insignificance of the interaction terms. Analogous to EU stock market reactions, the charter value of a bank described in H2$_{U.S.,l,stock}$ has no significant impact on U.S. shareholders.

Table 8: Determinants of Stock and CDS Market Reactions to Liquidity Risk Regulation

	Stock Market				CDS Market			
	Liquidity Events		Liquidity-Only		Liquidity Events		Liquidity-Only	
	CAR	CMAR	CAR	CMAR	ΔCAS	$\Delta CMAS$	ΔCAS	$\Delta CMAS$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: EU								
LCR_PROXY	0.0001	−0.0004	−0.002	−0.002	−0.037***	−0.028***	−0.034***	−0.035***
	(0.001)	(0.001)	(0.004)	(0.004)	(0.009)	(0.008)	(0.010)	(0.010)
NSFR_PROXY	−0.013	−0.009	−0.040*	−0.034*	0.061	−0.012	0.032	−0.039
	(0.011)	(0.012)	(0.022)	(0.020)	(0.053)	(0.053)	(0.040)	(0.034)
DEP_ASSET	−0.021	−0.025	−0.005	−0.002	−0.102*	−0.027	0.030	0.060*
	(0.014)	(0.016)	(0.023)	(0.022)	(0.053)	(0.042)	(0.052)	(0.033)
GIIPS	0.007**	0.005	0.011*	0.011*	−0.015**	0.002	−0.032***	−0.015
	(0.004)	(0.004)	(0.006)	(0.006)	(0.007)	(0.008)	(0.008)	(0.010)
SOV_DEBT	−0.024***	−0.024***	−0.026***	−0.026***	0.060***	0.042***	0.030***	0.025***
	(0.005)	(0.005)	(0.007)	(0.007)	(0.009)	(0.008)	(0.007)	(0.008)
GIIPS∗SOV_DEBT	−0.025***	−0.026***	−0.049***	−0.048***	−0.009	−0.002	0.045***	0.033***
	(0.008)	(0.008)	(0.013)	(0.012)	(0.013)	(0.013)	(0.009)	(0.011)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	702	702	480	480	177	177	118	118
R^2	0.097	0.095	0.134	0.132	0.338	0.348	0.326	0.422
Panel B: U.S.								
MOD_AFF_l	−0.119	−0.139	−0.116	−0.174				
	(0.125)	(0.128)	(0.140)	(0.147)				

FULL_AFF_l	0.127***	0.138***	0.236***	0.239***
	(0.038)	(0.040)	(0.066)	(0.072)
LCR_PROXY	−0.001	0.0002	0.001	0.002
	(0.003)	(0.003)	(0.003)	(0.003)
NSFR_PROXY	−0.028	−0.039*	−0.038	−0.043*
	(0.022)	(0.022)	(0.025)	(0.025)
DEP_ASSET	0.003	0.003	−0.008	−0.003
	(0.017)	(0.017)	(0.019)	(0.020)
MOD_AFF_l∗LCR_PROXY	−0.022	−0.037	−0.017	−0.028
	(0.021)	(0.025)	(0.029)	(0.034)
FULL_AFF_l∗LCR_PROXY	−0.042***	−0.041***	−0.040***	−0.038***
	(0.007)	(0.007)	(0.010)	(0.010)
MOD_AFF_l∗NSFR_PROXY	0.133	0.160	0.134	0.197
	(0.135)	(0.139)	(0.154)	(0.162)
FULL_AFF_l∗NSFR_PROXY	−0.134***	−0.145***	−0.252***	−0.262***
	(0.046)	(0.048)	(0.079)	(0.085)
Control	Yes	Yes	Yes	Yes
Obs.	2,629	2,629	1,818	1,818
R^2	0.051	0.056	0.064	0.070

This table presents the variables explaining heterogeneous reactions in the dependent variable, defined as either $CAR_{i,t}$, $CMAR_{i,t}$, $\Delta CAS_{i,t}$, or $\Delta CMAS_{i,t}$, across 13 liquidity events announced by the BCBS, for EU and U.S. banks. These values are calculated according to Eq. (3)–Eq. (10). Dependent variables are multiplied by -1 if the event is associated with a reduction in regulatory intensity. The MSCI World index is used as proxy for the stock market portfolio. The iTraxx Europe 5-years and the iTraxx CDX IG 5-years indices are used as proxies for the EU and U.S. CDS market portfolios, respectively. For so-called liquidity-only events, liquidity events are excluded (events 4, 5, 6, 11) if they are announced simultaneously with market and credit events. The bank-specific variables are LCR_PROXY, NSFR_PROXY and DEP_ASSET. LCR_PROXY is a proxy for a bank's LCR. NSFR_PROXY is a proxy for a bank's NSFR. DEP_ASSET is the ratio of customer deposits to total assets. The country-specific variables are GIIPS, MOD_AFF_l and FULL_AFF_l. GIIPS is a dummy variable that is 1 for EU banks located in Greece, Italy, Ireland, Portugal or Spain and 0 otherwise. MOD_AFF_l is a dummy variable that is 1 for U.S. banks that are subject to modified liquidity metrics and 0 otherwise. FULL_AFF_l is a dummy variable that is 1 for U.S. banks that are subject to full liquidity metrics and 0 otherwise. SOV_DEBT is a dummy variable that is 1 for the sovereign debt crisis (2010-05-02–2013-06-30) and 0 otherwise. The control variables are SIZE, COST_INC, ROA and dummies for the subprime crisis (2007-06-01–2008-09-14) and the GFC (2008-09-15–2010-05-01) for EU portfolios, while U.S. portfolios also include the sovereign debt crisis dummy. SIZE is the natural logarithm of total assets. COST_INC is the cost-to-income ratio. ROA is the return on assets. Regressions are estimated using random effects with clustered standard errors at bank level reported in parentheses. Computed p values are based on a two-sided significance test: $^{*}p$<0.1; $^{**}p$<0.05; $^{***}p$<0.01.

2.7 *Further Robustness and Limitations*

In the main section, abnormal stock and CDS market reactions are calculated using different models and indices to avoid dependency on exogenous decisions. Nevertheless, the results could be biased because of event-induced volatility as well as cross-sectional and serial correlation (Hippert and Uhde, 2021). To account for volatility clustering and autoregressive heteroscedasticity in the time series of returns and CDS spread changes, abnormal stock and CDS market reactions are recalculated using a generalized autoregressive conditional heteroscedasticity (GARCH) model (Farruggio et al., 2013). Hence, Eq. (3), Eq. (4) and the CDS single-index model are estimated using a GARCH(1,1) model, revealing that signs and effect sizes of aggregated stock and CDS market reactions remain comparable in most cases. Then the cross-sectional regressions are recalculated with dependent variables calculated with the GARCH(1,1) model. The conclusions remain consistent in most cases.[39] The analysis of CDS market reactions is limited because it focuses solely on major banks in the U.S. and Europe. Therefore, conclusions regarding increased risk due to regulation are specifically applicable to major banks, which are more likely than smaller banks to be rescued. Furthermore, a challenge emerges within the U.S. context, given the small sample size, as this category consists of only eight banks. In the interpretation of the results, careful consideration is given to the potential influence of confounding events on the observed market reactions.

The CDS market is opaque and illiquidity has increased in recent years, which can lead to rising CDS spreads (International Swaps and Derivatives Association, 2023). Paddrik and Tompaidis (2019) show that post-GFC regulation increased the costs of holding inventory for dealers, thereby increasing illiquidity. Although this problem is mitigated in this analysis by applying liquidity criteria to the CDS portfolios, the majority of market makers and dealers are themselves banks (European Securities and Markets Authority, 2023). Because regulation increases costs for banks, ceteris paribus, inventory costs also increase, thereby increasing CDS market illiquidity. This could imply that the observed increased CDS spreads following the regulatory announcements do not stem from an increase in risk but rather from the regulation-induced rise in illiquidity. If this increase is attributed to heightened illiquidity, then the CDS spreads of all firms, not just banks, would rise. The EU CDS market reaction to credit risk regulation is the only significant one. To assess whether this reaction is caused by an increase in risk or heightened illiquidity, a CDS portfolio consisting of 27 non-financial firms is constructed, mimicking the countries of origin of the banks.[40] The results suggest that the banks' CDSs have risen due to an increase in risk, because no CDS market reaction of the non-financial portfolio is positive and significant.[41]

[39] Analyses can be provided upon request.

[40] CDS illiquidity is more severe for non-financial firms, hindering the creation of a liquid portfolio covering all 26 credit events. Eaton Corporation has been headquartered in Ireland only since 2012.

[41] Results can be provided upon request. The conclusions do not change when the CDS market reaction is calculated using the single-index model.

The main section already addresses bank-specific confounding events. However, a key difference between U.S. and EU banks is that since 2014, the ECB has supervised large Eurozone banks as part of the SSM. In this study, to ensure that EU reactions are not influenced by the introduction of the SSM, following Fiordelisi et al. (2017), 25 significant events are identified. None of the three-day windows for market, credit, and liquidity regulations overlap with these events, ruling out SSM-related biases in the results.

2.8 Conclusion

With the full release of the BCBS's regulatory frameworks for market, credit, and liquidity risk through Basel II.5, Basel III, and Basel IV, market reactions can be studied to understand the real-world impact of regulation on shareholders and creditors, which is essential for evaluating its effectiveness. This paper picks up here using event study methodology to quantify the collective impact of 15 market events, 26 credit events, and 13 liquidity events for EU and U.S. bank stocks and CDSs. The findings significantly contribute to the literature on financial regulation post-GFC. First, the findings demonstrate that regulation of financial risks leads to notable market reactions from shareholders and creditors, indicating changes in profitability and risk, whereby bank- and country-specific factors explain individual responses. Second, significant differences in market reactions between the EU and the U.S.—largely attributable to varying implementation practices—raise questions about the establishment of a true level playing field. Finally, the reactions can be discussed in the context of whether the regulatory objectives of reducing risk for the public sector have been achieved.

The analysis reveals significant negative stock market reactions for EU banks in response to market and credit risk regulation. This stands in contrast to U.S. banks, which exhibit insignificant reactions to market risk and a less stringent response to credit risk. The stricter application of Basel regulations in the EU, coupled with the Volcker Rule and exemptions or relief for smaller banks in the U.S., account for much of this discrepancy. Creditors in both the EU and U.S. show no reaction to market risk regulation. However, credit risk regulation triggers a significant rise in EU CDS spreads, indicating that creditors perceive higher risks due to diminished bailout expectations. In contrast, U.S. creditors respond with increased but insignificant CDS spreads, likely because the Dodd-Frank Act had already lowered bailout expectations prior to the Basel reforms. Liquidity regulation shows no significant impact on shareholders and creditors in both the EU and U.S. The absence of a U.S. market reaction may stem from U.S. liquidity rules applying only to large banks, which had stronger liquidity positions during and post-GFC compared to EU banks. While earlier studies find a negative EU shareholder response, this paper detects no effect, suggesting that the additional events examined here have limited market relevance. Although CDS spreads increased similarly to previous findings, no statistical significance is observed, likely due to methodological differences and sample variations.

Importantly, the cross-sectional analysis demonstrates that bank- and country-specific factors play a crucial role in heterogeneous responses to regulation, highlighting the complexity of regulatory impacts across different banking institutions and jurisdictions. Regarding market risk regulation, a bank's capitalization reduces CDS spreads in both the U.S. and the EU. Additionally, higher market risk and a bank's classification as a G-SIB increase U.S. CDS spreads. Conversely, U.S. stock market reactions are negatively influenced by G-SIBs, while higher market risk and a bank's location in GIIPS reduce returns for EU shareholders. Regarding credit risk regulation, there is a positive but diminishing effect of a bank's capitalization on U.S. stock market reactions, while higher risk costs have a negative impact. Additionally, banks that are subject to regulation show lower returns compared to SBHCs. U.S. creditors respond to increased risk costs with higher CDS spreads. In the EU, the feedback loop positively influences shareholders and reduces CDS spreads. Bank capitalization and risk costs also exert a negative impact. Regarding liquidity risk, a negative impact of more liquid balance sheets and charter values on EU CDSs is observed, indicating greater resilience to liquidity shocks. In contrast, the feedback loop increases creditor risk. For the EU stock market, a negative effect of the feedback loop is evident, which similarly applies to reduced funding mismatches. In the U.S. stock market, a negative effect is found for large banks subject to full liquidity requirements, indicating a one-sided penalty and competitive disadvantage.

Overall, the findings suggest that the Basel reforms post-GFC have successfully transferred risks from taxpayers back to shareholders and reduced moral hazard among creditors, indicated by the negative stock market reactions and increased CDS spreads, which is consistent with the public interest theory by Needham (1983). The effect is more pronounced in the EU than in the U.S., which is due to the previously introduced Dodd-Frank Act and the stricter implementations of regulations in the EU. However, the evident differences in implementation raise concerns about the establishment of a level playing field. Consequently, a critical policy implication emerges: there is a need for more consistent regulatory enforcement across BCBS member states.

2.9 Declaration of Author and Record of Accomplishments

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Share of Contributions:

Contributions	**Jonas Krettek**
Research design	100%
Development of research question	
Method development and specification	
Research performance & analysis	100%
Literature review and framework development	
Data collection, preparation and analysis	
Analysis and discussion of results	
Derivation of implications and conclusions	
Manuscript preparation	100%
Final draft	
Finalization	
Overall contribution	100%

Date, Jonas Krettek

3 Surprise, Surprise? Banks' and Insurers' Market Reactions to Interest Rate Hikes

3.1 Abstract

In response to persistently high inflation due to the COVID-19 pandemic and the Russian attack on Ukraine, central banks implemented a series of interest rate hikes starting in 2022. These measures aimed to curb inflation but also had significant implications for financial markets. The paper examines the impact of interest rate hikes by the ECB and the Fed on the stocks and CDSs of Eurozone and U.S. banks and insurers. Using an event study, we analyze CARs and ΔCAS from 2022 to 2023. Since market expectations shape reactions, we use factor analysis to isolate monetary shocks, which help to explain market reactions. Our results indicate that monetary policy decisions have direct and significant effects on the stocks and CDSs of banks and insurers. While an interest rate increase exceeding market expectations exerts downward pressure on stock prices and raises risk premiums (CDS spreads), a lower-than-expected rate hike leads to rising stock prices and declining risk premiums. Additionally, we identify significant spillover effects from Fed announcements into Eurozone markets and vice versa, highlighting the global interconnectedness of financial markets.

3.2 Introduction

The global economy has experienced economic distress in recent years, primarily driven by surging inflation and geopolitical uncertainties following Russia's invasion of Ukraine. The initiation of the conflict in early 2022 exacerbated pre-existing inflationary pressures that had emerged during the COVID-19 pandemic, as major economies, particularly countries of the Eurozone and the U.S., imposed economic sanctions on Russia. These developments led to rising energy and commodity prices, disruptions in global supply chains, and overall economic instability. These factors contributed significantly to the inflation surge: in October 2022, the inflation rate in the Eurozone peaked at 10.6%, while in the U.S., it had already reached its highest level of 9.1% in June 2022. In response to persistent inflationary pressure, numerous central banks were compelled to adjust their monetary policy strategies. The Fed initiated a period of monetary tightening, raising the federal funds rate to its highest level in decades. The ECB followed suit on July 21, 2022, implementing its first interest rate hike after a period of historically low and, at times, negative interest rates. These measures aimed to curb inflation and restore price stability.

The impact of monetary policy decisions on financial markets is a central topic in economic research. Numerous studies demonstrate that monetary policy interventions have significant implications for capital markets, with rising interest rates typically leading to declining stock prices (e.g. Thorbecke, 1997; Angeloni and Ehrmann, 2003; Rigobon and Sack, 2004; Bernanke and Kuttner, 2005). One strand of literature focuses on general stock market reactions without accounting for sectoral differences. For instance, the effects on stock indices such as the S&P 500 or the STOXX50E are examined (Gürkaynak et al., 2005; Altavilla et al., 2019; Swanson, 2021). Banks and insurers play a crucial role in monetary policy transmission due to their intermediation and risk transformation functions, which influence investment and consumption. Consequently, they are considered primary targets of monetary policy interventions (Yin et al., 2010; Yin and Yang, 2013; Ricci, 2015). It is therefore not surprising that another strand of literature analyzes the effects of monetary policy on financial institutions, showing significant effects in both the U.S. and Europe (e.g., (Aharony et al., 1986; Akella and Greenbaum, 1992; Fiordelisi et al., 2014; Ricci, 2015; English et al., 2018; Bats et al., 2023) for banks; (Brewer et al., 2007; Czaja et al., 2009; Jensen et al., 2019; Killins and Chen, 2022) for insurers).

However, the existing literature predominantly adresses interest rate cuts. Prior research has shown that the mechanisms underlying rate cuts and rate hikes are not symmetric (Yin and Yang, 2013; Ricci, 2015). While rate cuts typically serve as an economic stimulus, interest rate hikes tighten financing conditions, increase capital costs, and may lead to liquidity constraints. Consequently, the effects of rate hikes cannot simply be inferred from studies on rate cuts. Moreover, the few studies that explicitly examine interest rate hikes (Aharony et al., 1986; Akella and Greenbaum, 1992; Ricci, 2015; English et al., 2018) are based on observation periods preceding the recent tightening cycles. The interest rate increases implemented by the ECB and the Fed since 2022 represent a significant monetary policy paradigm shift. This shift is characterized by the central banks' departure from a long-standing expansionary, growth-oriented monetary policy toward a restrictive approach focused on combating inflation. This transition was evident in the rapid and substantial increase in key interest rates. The resulting economic and financial implications are far-reaching and mark a distinct break from the monetary policy strategies pursued over the past decades. The implications of this shift for banks and insurers remain largely unexplored. A new empirical study is therefore necessary to analyze whether and to what extent the current interest rate hikes trigger market dynamics.

Another critical gap in the literature concerns the cross-border transmission of monetary policy decisions. Most studies focus on individual economic regions, such as the U.S. or Europe, and examine the domestic effects of monetary policy measures. However, potential spillover effects between these two highly integrated markets remain largely unaddressed. While some authors analyze spillover effects from the Fed policy into European markets (Conover et al., 1999; Ammer et al., 2010; Hausman and Wongswan, 2011), these studies predominantly focus on non-financial sectors. Furthermore, the impact of ECB policy on non-euro markets remains largely unexplored, with only Groba and Serrano (2020) examining its effect on the default risk of U.S. firms. This shortcoming is also highlighted by Altavilla et al. (2019). Since banks and insurers act as transmitters of monetary policy, examining the cross-border transmission of monetary shocks in this sector is particularly relevant. Banks influence investment behavior through lending, while insurers play a central role in capital markets as institutional investors and risk buyers.

A further shortcoming of the existing literature is its exclusive focus on stocks, reflecting only changes in profitability. Our study expands upon this approach by incorporating CDS spreads, which reflect changes in creditors' risk perception. Koch and Islam (2024) examine the impact of federal funds rate changes on bank risk, concluding that interest rate hikes increase bank risk. However, their analysis is limited to the U.S. market and focuses exclusively on banks, neglecting insurers and cross-border effects. Moreover, the authors use alternative proxies for bank risk instead of CDS spreads. Our study integrates all these perspectives to provide a comprehensive assessment of how interest rate hikes affect both stocks and CDSs, offering a more holistic view of monetary policy's impact on the financial sector.

In summary, the study's contribution is as follows: First, we analyze the stock and CDS market reactions of Eurozone and U.S. banks and insurers to interest rate hikes by the ECB and the Fed using an event study approach. For each event, we compute CARs and ΔCAS for each firm i as well as the average for the respective portfolio. Second, we investigate cross-border spillover effects by examining the transmission of the Fed's monetary policy into Eurozone markets and vice versa. Lastly, we construct monetary policy shocks for the ECB and the Fed, which are used in the cross-sectional analysis to more precisely examine the responses of shareholders and creditors.

We focus on the ECB and the Fed due to their central role in the global financial system. As issuers of the two most important global currencies, their monetary policy decisions have far-reaching effects on international capital markets. Additionally, the U.S. and European financial markets are among the largest and most liquid, making them particularly sensitive to interest rate changes. The observation period begins with the first interest rate hikes by the central banks in 2022 and extends to their final monetary policy meetings in December 2023. This timeframe is chosen to exclusively analyze the phase of rising interest rates. Both central banks refrained from further rate hikes in their last meetings of 2023, and by the end of the year, markets had already begun to speculate about potential rate cuts. Thus, the period of monetary tightening was effectively concluded.

Since financial markets price in expected rate changes ex ante, only unexpected monetary policy decisions generate significant market reactions. To identify unexpected ECB interest rate shocks, we utilize the Euro Area Monetary Policy Event-Study Database (EA-MPD) and the framework developed by Altavilla et al. (2019). We calculate the Fed interest rate shocks following the methodology of Gürkaynak et al. (2005), using the pre-estimated shocks made available by Acosta et al. (2024). The cross-sectional analysis employs these shocks to investigate the CARs and ΔCAS in greater detail.

Overall, our results suggest that interest rate hikes by the Fed and the ECB negatively affect domestic stock returns, with banks and insurers showing differentiated responses due to their distinct business models and varying sensitivities to interest rates. With respect to creditors, interest rate hikes tend to increase domestic CDS spreads, although the responses are somewhat more nuanced. Finally, we identify significant spillover effects from Fed announcements into Eurozone stock and CDS markets and vice versa, underscoring the strong interconnectedness of global financial markets. Notably, the direction and magnitude of the responses are not necessarily consistent with those observed among domestic shareholders and creditors. The cross-sectional analysis indicates that monetary policy shocks play a significant role in explaining CARs and ΔCAS. Furthermore, the analysis allows for a quantification of the relative influence of conventional versus unconventional monetary policy shocks, and provides insights into which specific components of monetary policy most strongly affect stock and credit markets.

The remainder of the paper is structured as follows: Section 3.3 provides the theoretical background by outlining the development of interest rates and discussing potential financial market reactions. Section 3.4 presents the data and methodology used in the analysis. Section 3.5 reports the empirical results, while Sec. 3.6 addresses the study's limitations and robustness checks. Finally, Sec. 3.7 concludes.

3.3 Theoretical Background

3.3.1 Interest Rate Turnaround

Monetary policy decisions are typically made by the central bank of the respective country. For the Eurozone, the ECB decides on monetary policy. The primary objective of the ECB is to maintain a stable price level, aiming for a medium-term inflation of 2%, whereby the primary instrument is the setting of policy rates. The Governing Council of the ECB convenes every six weeks to make monetary policy decisions. Three different policy rates can be distinguished. The interest rate for the main refinancing operation (MRO) refers to the rate at which banks can borrow funds on a weekly basis against collateral at a pre-determined interest rate. The rate for the marginal lending facility (MLF) allows banks to borrow overnight credits at a pre-defined interest rate. This rate is regularly higher than the rate for MRO. The deposit facility (DF) rate enables banks to store overnight deposits at a pre-defined interest rate. This rate is typically lower than the rate for MRO. If the ECB decides to increase the policy rate during its meetings, it means a simultaneous increase in all three interest rates by the same factor. The development of these interest rates up to December 31, 2023, is shown in Fig. 2.

July 21, 2022, marked the end of the negative interest rate policy that had been in place for several years. The increase in interest rates had been preceded by two meetings where there were initial indications of an imminent rate hike, making the eventual increase potentially not a surprise event. Within the observation period, there were nine more rate hikes, and since September 14, 2023, the MRO rate has been held constantly at 4.50%.

Unlike the ECB, the Fed operates under a dual mandate. Besides ensuring price stability, it also aims to achieve maximum employment. The Fed primarily uses the federal funds rate as its key monetary policy tool. Set by the Federal Open Market Committee (FOMC), this rate determines the interest at which depository institutions lend to one another. Unlike in other systems, the Fed sets a target range rather than a fixed rate. The FOMC meets eight times a year as scheduled to

Figure 2: ECB Interest Rate Announcements

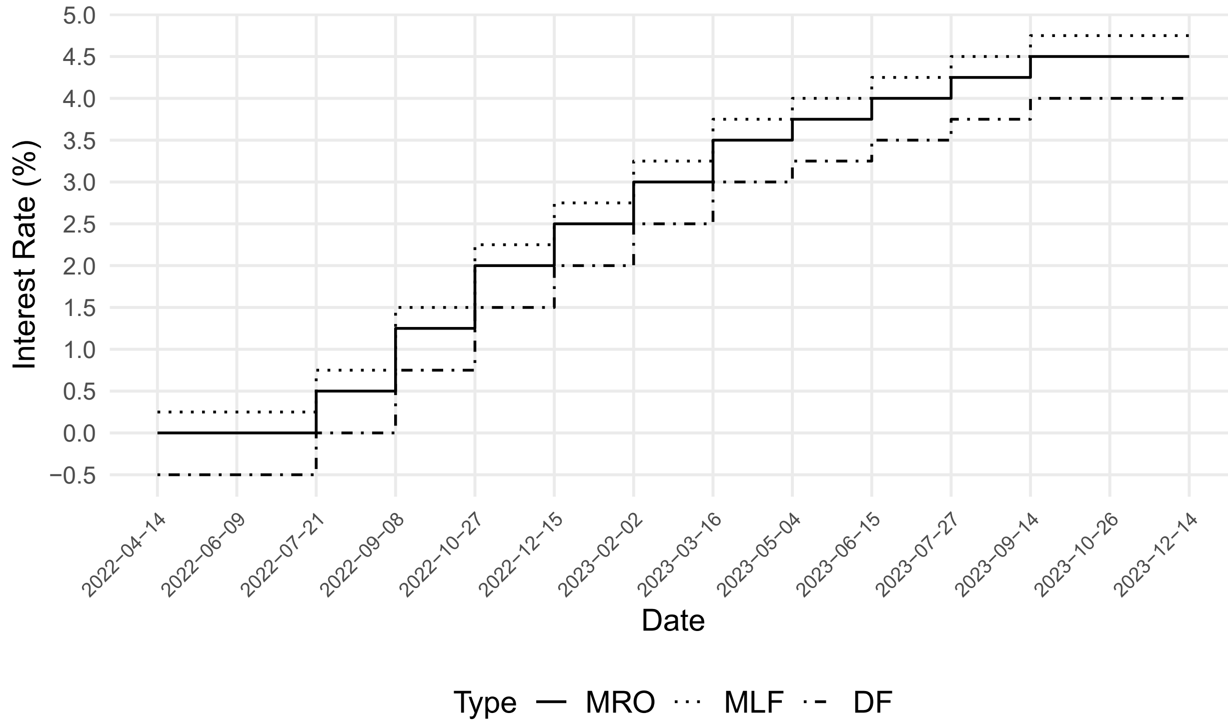
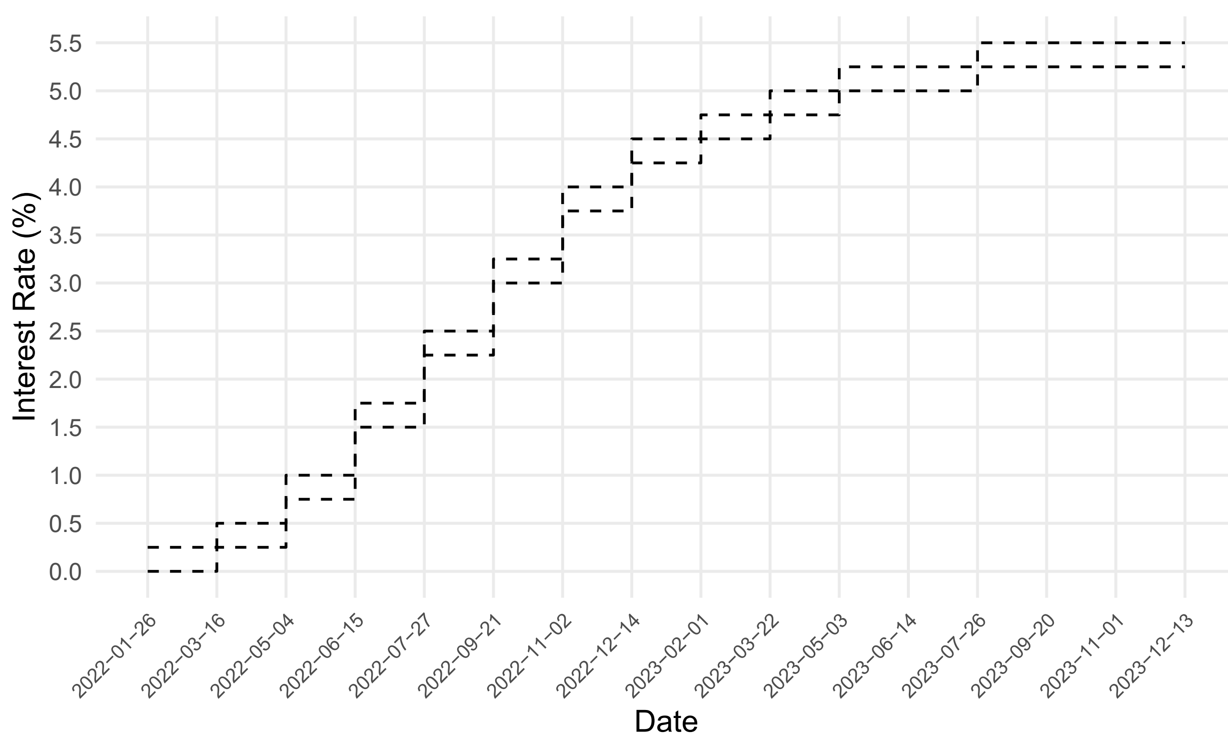


Figure 3: Fed Interest Rate Announcements



analyze economic developments and make monetary policy decisions. The development of the federal funds rate, shown in Fig. 3, reflects these adjustments.

As evident from Fig. 3, the federal funds rate was increased for the first time on March 16, 2023. However, in the FOMC announcement of January 2022, there were initial indications that interest rates would be raised in the future. Continuous interest rate hikes followed until July 26, 2023 (with one exception on June 14, 2023), resulting in a federal funds rate range of 5.25% to 5.5% in the U.S. from that point onward.

3.3.2 Capital Market Reactions

3.3.2.1 Surprising vs. Anticipated Interest Rate Changes and Spillover Effects

Before delving into the theoretical foundations explaining market reactions, it is essential to distinguish between anticipated and unexpected interest rate changes. Since the dates for monetary policy announcements are known in advance, investors form expectations about whether and to what extent interest rates might be adjusted ex ante, which allows investors to hedge against potential risks (Kim et al., 2013). According to the efficient market hypothesis, market prices reflect all available information including the forward-looking expectations of investors (Fama, 1970). Therefore, markets react only significantly if actual interest rate decisions deviate from expectations. Numerous studies have shown that only the unexpected components of an interest rate hike impact asset prices, while anticipated changes in central bank rates elicit little to no reaction (Aharony et al., 1986; Akella and Greenbaum, 1992; Jensen et al., 1996; Thorbecke, 1997; Bomfim, 2003; Ehrmann and Fratzscher, 2004; Rigobon and Sack, 2004; Bernanke and Kuttner, 2005; Boyd et al., 2005; Wongswan, 2009; Sondermann et al., 2009; Chuliá et al., 2010; Kim et al., 2013; Altavilla et al., 2019; Swanson, 2021). This has been particularly documented in the literature for stocks, while the mechanism is analogously applicable to creditors and, consequently, to CDSs as well.

Beyond conventional monetary policy, market reactions to unconventional monetary policy measures are also expected to occur only if such announcements are unexpected. These announcements are made by the ECB and the Fed alongside policy rate decisions. Examples include forward guidance (FG) and extensive asset purchase initiatives. FG refers to the communication by central banks regarding the future path of monetary policy. Examples of the latter instrument include quantitative easing (QE) in the Eurozone and the large-scale asset purchase (LSAP) program in the U.S. Unconventional monetary policy was particularly employed by central banks following the GFC of 2008, as an attempt to stimulate the economy during the zero lower bound period.

Another key aspect of our analysis concerns the potential spillover effects from the Fed's monetary policy to Eurozone markets, and vice versa. Interest rate decisions in one economic zone influence financial intermediaries in others through several channels. Large banks and insurers with cross-border operations, such as subsidiaries, are directly impacted by foreign central bank policies. Exchange rates form another channel: changes in interest rates, ceteris paribus, shift the EUR/USD exchange rate, prompting capital flows between the Eurozone and the U.S. Additionally, financial intermediaries often rely on international financing, and changes in interest rates, such as those by the Fed, alter the cost structures of European banks and insurers. Monetary policy, whether contractionary or expansionary, aims to achieve real economic effects. For example, an ECB rate hike could slow Eurozone growth, indirectly affecting U.S. banks and insurers financing or underwriting exporters or firms engaged in European business. This applies equally when intermediaries are directly involved in European operations. Finally, the correlation of asset prices creates another channel: interest rate changes influence bond and stock prices, affecting asset valuations even beyond a central bank's immediate reach.

Hence, market participants also monitor decisions of internationally significant central banks. Previous research confirms that U.S. monetary policy has global implications on financial markets, with foreign firms on average reacting similarly to U.S. interest rate announcements as domestic firms (Ammer et al., 2010). Due to the significance of the European market, it can be assumed that U.S. financial intermediaries also respond to changes in the ECB's interest rate policy.

3.3.2.2 Impact of Interest Rate Changes on the Pricing of Stocks and CDSs

We now outline the theoretical considerations as to why shareholders and creditors should generally react and why these reactions may be particularly pronounced in the case of banks and insurers. Reactions in the stock market arise from the pricing of those stocks. Its fair value corresponds to the present value of the future expected cash flows. A change in this fair value, and consequently in the stock price, occurs due to changes in the discount rate on the one hand and adjustments to future expectations of cash flows on the other (Lobo, 2000; Ehrmann and Fratzscher, 2004; Crowder, 2006; Yin et al., 2010; Laeven and Tong, 2012). We first address changes in the discount rate.

Due to the positive correlation between the policy rate and the discount rate, an increase in the policy rate leads to a rise in the discount rate (Thorbecke, 1997; Lobo, 2000; Yin et al., 2010). This effect arises because the discount rate corresponds to the required return of equity investors (Yin et al., 2010). According to the CAPM, the required return of investors consists of the risk-free rate and a risk premium on the risk-free rate. An increase in the policy rate raises the required return of investors for two main reasons: First, there is a strong positive correlation between the risk-free rate and the policy rate (Yin et al., 2010). Second, higher policy rates increase bond yields, further raising the required return of stock investors through increasing opportunity costs (Cook and Hahn, 1989; Thornton, 1998; Kuttner, 2001). This means that fixed-income securities become more attractive compared to stocks, and especially risk-averse investors, ceteris paribus, prefer bonds. Thus, stock prices would decrease.

However, future cash flows can also be affected by interest rate changes and we initially present firm-internal factors. In this case, the actual reaction of stock prices remains unclear, as this largely depends on the firm's business model, its specific portfolio and sensitivity to interest rates. Given that we are analyzing banks and insurers, whose business models are highly sensitive to interest rates, there are also arguments for rising stock prices. Therefore, determining the overall effect of interest rate changes on stock prices is challenging.

Another reason why it is difficult to make statements about stock market reactions is because monetary policy decision can be perceived by market participants in two ways that trigger different stock reactions: either as a genuine monetary policy shock or as a revelation about the actual state of the economy (Altavilla et al., 2019). The latter type of shock, in line with Miranda-Agrippino and Ricco (2021) and Jarociński and Karadi (2020), is referred to as an information shock. We have thus far discussed the effects of a genuine monetary shock, considering changes in the discount rate and the resulting shifts in future cash flows. Even against this backdrop, the overall effect on stock markets remains unclear. Additionally, monetary shocks can be interpreted as an information shock. As a genuine monetary shock, an interest rate cut might be perceived positively by shareholders due to the lower discount rate (assuming that, ceteris paribus, future cash flows remain unchanged). However, conversely as an information shock, it could also be viewed as a signal that economic conditions are worse than previously assumed (Altavilla et al., 2019). The consequence is a negative reaction, as a deteriorating economic outlook implies lower expected dividends. Vice versa, an interest rate hike, perceived by the market as a genuine monetary shock, leads to declining stock prices due to an increasing discount rate (assuming constant future cash flows). However, as an information shock, markets interpret rising interest rates as a sign of economic recovery, promising higher future cash flows, and thus stock prices would increase. Ultimately, this perspective is closely linked to expectations regarding future cash flows, with the reason being macroeconomic in nature.

To assess the impact on financial intermediaries' risk, we utilize CDSs. In the next step, we examine the theoretical mechanism of CDS pricing before specifically addressing banks and insurers. CDSs are OTC default insurance for debt, triggering a payout upon a predefined event. The protection buyer pays periodic premiums to the seller, receiving compensation if the reference obligation defaults before contract maturity. The periodic premium, called spread, is quoted in bps and reflects credit risk. CDS spreads fluctuate in response to changes in the underlying risk associated with the issuing firm. It is plausible to assume that the risk of firms changes when central banks adjust the interest rate.

Similar to stocks, the overall impact on the CDS market reaction is theoretically uncertain, as changes in risk levels are largely influenced by a firm's interest rate sensitivity and business model—both of which shape its future cash flows and risk profile. We discuss this separately for banks and insurers. In addition to changes in future cash flows, creditors may also perceive monetary policy adjustments as an informational shock: a rate cut could be interpreted as a signal of a deteriorating economic outlook. In this case, creditors respond with increasing CDS spreads, i.e. higher risk perception. Vice versa, interest rate hikes could provoke CDS spreads to decrease.

Following the general discussion of stock and CDS market reactions, the subsequent sections examine the specific responses of banks and insurers. The precise consequences of an interest rate hike on stock prices and CDS spreads remain unclear. They depend on whether markets perceive a textbook monetary shock or an informational shock, and which of the various channels dominates in the discussion of expected future cash flows.

3.3.2.3 Banks' Reactions

A banks' interest rate sensitivity arises from the mismatch of assets and liabilities. Banks typically hold long-term fixed-rate loans, which they refinance through short-term variable-rate deposits. The resulting spread between loans and deposits is the basis for banks' net interest income. Due to the strong correlation between policy rates and market interest rates, which banks use to set deposit and lending rates, banks adjust their interest rates accordingly in response to central bank rate changes (Mojon, 2000; Yin et al., 2010; Bats et al., 2023). Interest pass-through models and empirical research suggest that loan rates tend to respond more strongly and swiftly to changes in interest rates than deposit rates, particularly during periods of monetary tightening (Albertazzi and Gambacorta, 2009; Bolt et al., 2012; Busch and Memmel, 2017; English et al., 2018; Dräger et al., 2021; Deutsche Bundesbank, 2023). This implies that when policy rates increase, banks adjust their lending rates more quickly than their deposit rates, leading to a temporary widening of net interest margins. While this pattern aligns with empirical findings, it seemingly contradicts the fundamental intuition of positive maturity transformation, which would suggest that deposit rates, due to their short-term nature, should be adjusted more rapidly than loan rates. However, in practice, banks often delay deposit rate adjustments to preserve profitability, whereas loan rates—especially those on new or variable-rate loans—tend to reflect monetary policy changes more immediately. Consequently, the asymmetric pass-through of interest rates leads to a temporary advantage for banks in times of interest rate hikes. This increase in net interest income leads to increases in expected future cash flows and, consequently, stock prices (Dechow et al., 1998; Fama and French, 2006; Doukakis et al., 2020). This contrasts with the generally negative impact of interest rate hikes on stocks due to a higher discount rate, as previously discussed. As higher profits reduce the probability of default (PD), banks' creditors would react with decreasing CDS spreads. However, an increase in interest rates may lead to depositors withdrawing their funds, as investors seek more attractive alternatives with higher returns, thereby forcing banks to raise deposit rates after a certain delay as well (Koont et al., 2024; Koch and Islam, 2024). Consequently, the positive effect on net interest income might be temporally limited and depends on the the competitive situation.

An increase in policy rates can lead to capital losses in banks' trading portfolios as the market value of bonds and stocks declines, requiring losses to be covered by equity. Beyond trading losses, higher interest rates also impact credit quality—a key driver of credit portfolio losses (Hoggarth et al., 2005). As fixed interest rates expire, banks pass higher rates on to borrowers, increasing the risk of defaults and loan write-offs. New borrowers face higher borrowing costs, which can lead to adverse selection and moral hazard, further deteriorating credit quality (Stiglitz and Weiss, 1981). Losses exceeding expectations must be absorbed by equity. For banks holding foreign currency assets, rising interest rates amplify conversion differences (English et al., 2018; Koch and Islam, 2024). Capital losses in both trading and credit portfolios, alongside currency translation adjustments, impair earnings and weaken investor expectations about future cash flows, ultimately lowering stock prices. As reduced earnings increase banks' PD, CDS spreads are expected to rise.

This problem of declining credit quality is closely tied to the reduction in credit supply, which we explore in the following. Changes in economic conditions shape banks' lending behavior and this perspective is linked to the concept of an information shock, as discussed in the previous section. Empirical evidence suggests that banks typically reduce credit supply in response to contractionary monetary policy (Flannery and James, 1984; Bernanke and Blinder, 1988; Kashyap and Stein, 1995, 2000; Nilsen, 2002). This observation is attributable to the agency costs associated with lending, which constitute a portion of the external financing costs for borrowers. Contractionary monetary policy reduces the net worth and solvency of potential borrowers, thereby increasing the perceived risk associated with lending to them (Bernanke et al., 1996). As a result, banks are compelled by regulatory requirements and their own risk appetite to demand higher risk premiums, leading to increased financing costs for borrowers. Moreover, as already explained, contractionary monetary policy results in a reduction of bank deposits, which are essential for the refinancing of loans (Bernanke and Blinder, 1988). In light of these two observations, banks could reduce their aggregate credit supply and increasingly invest in safer alternatives (Bernanke and Gertler, 1989). This credit rationing, similar to the quality of the credit portfolio, can also be explained by adverse selection and moral hazard on the part of borrowers (Stiglitz and Weiss, 1981).

In addition, the demand from potential borrowers could decline, as they are no longer able to service the loans due to the increased financing costs. These two effects on bank lending lead to lower interest income for banks, which negatively impacts the profit and, consequently, may in turn be reflected in declining stock prices. The lending behaviour also affects the perceived risk as the proportion of loans to total assets of a bank is considered a key driver of bank risk (Baselga-Pascual et al., 2015). Studies empirically demonstrated a positive correlation between the relative loan share and bank risk (Blaško and Sinkey Jr., 2006; Männasoo and Mayes, 2009). This implies that the altered lending policy reduces credit risk and subsequently results in a decline in the CDS spreads of banks. On the other hand, an excessive reduction in net interest income due to a rising PD could also drive up CDS spreads.

3.3.2.4 Insurers' Reactions

Similar to banking, insurers exhibit overall high interest rate sensitivity (Samuelson, 1945; French et al., 1983; Czaja et al., 2009). This observation can be explained by the insurance-specific business model: insurance companies receive premium payments and invest these in assets with different maturities to hedge against interest rate risks (Möhlmann, 2021). The majority of these assets consist of fixed-income securities (Brewer et al., 2007; Becker and Ivashina, 2015; Jensen et al., 2019; Becker et al., 2022). The resulting returns are then used to cover cash outflows and unexpected liquidity constraints due to obligations from insurance contracts (Killins and Chen, 2022; Kubitza, 2023).

Due to this business model, changes in interest rates have a significant impact on both the asset and liability sides of the balance sheet. This, in turn, affects expected cash flows and consequently influence the stock prices and CDS spreads of insurance companies.

On the asset side of the balance sheet, rising interest rates lead to higher yields on newly acquired bonds (Jensen et al., 2019). This suggest that stock prices increase, as higher returns positively influence investors' expected cash flows. CDS spreads would decline, as higher yields are associated with a reduced PD. However, bonds already held in the portfolio must be discounted at a higher interest rate. This results in a decline in the present value of these assets. Since bonds are, in most cases, recorded at amortized cost in the balance sheet, insurers accumulate hidden losses, which negatively impact their earnings capacity. These hidden losses lead to implicit losses, effectively reducing economic equity and increasing leverage. Consequently, the insurance company may be perceived by investors and creditors as riskier and less stable, leading to a decline in stock prices and an increase in CDS spreads.

In addition, there are impacts on the liability side. Since not only the assets but also the long-term liabilities of insurers are discounted, an interest rate hike leads to a reduction in the present value of these obligations as well. Due to the negative duration gap, which is typical for insurance companies, the decline in the present value of liabilities is greater than the decrease in the present value of assets (Koch and MacDonald, 2015). This results in a strengthening of the insurer's equity position, thereby improving its solvency and financial stability. Consequently, this should have a positive impact on investors' expectations, leading to an increase in stock prices. At the same time, the improved solvency reduces the perceived risk, which should be reflected in declining CDS spreads.

Notably, life insurers—particularly in Europe—occupy a unique position due to their business model. Many European insurers are obligated to guarantee their policyholders a minimum return over the duration of the contracts, requiring them to adopt appropriate investment strategies to meet these commitments (Möhlmann, 2021; Killins and Chen, 2022; Kaufmann et al., 2024). In contrast, U.S. life insurers typically do not offer fixed return guarantees but instead adjust their payouts in line with prevailing market interest rates. During the recent period of low interest rates, the challenge arose that the promised minimum returns could no longer be achieved, leading to financial strain for the affected insurers (Killins and Chen, 2022). In contrast, an increase in interest rates facilitates the attainment of the required returns, enabling insurers to dissolve existing interest rate reserves and strengthen their solvency ratio. This development has medium- to long-term positive effects on expected cash flows and, consequently, on the stock returns (Federal Financial Supervisory

Authority, 2023). Additionally, the reduction in perceived risk should lead to a decline in CDS spreads. However, it should be noted that both the assets and liabilities of life insurers exhibit a higher duration compared to other insurance companies, which entails specific consequences (Jensen et al., 2019). First, life insurers can only benefit from higher capital market returns in their investments with a time lag, as they have predominantly invested in long-term fixed-income bonds due to the longer duration of their liabilities (Jensen et al., 2019; Möhlmann, 2021; Killins and Chen, 2022). Second, the present values of fixed-income bonds with longer maturities are particularly sensitive to interest rate changes, as future interest payments must be discounted over a longer period. As a result, hidden losses arise on a larger scale (Federal Financial Supervisory Authority, 2023). Since the positive effects for life insurers materialize only with a delay and interest rate increases have a stronger impact on their valuation due to the long-term nature of their liabilities and assets, it can be assumed that their stocks and CDSs react more intensely to interest rate changes. Furthermore, this effect is likely to persist in the respective markets over an extended period.

All the further aspects concerning asset quality and foreign exchange position in the context of banks equally apply to (life) insurance companies.

3.4 Methodology

3.4.1 Data and Sample Selection

To measure capital market reactions, daily stock prices and CDS spreads of all available U.S. and Eurozone financial intermediaries are gathered using Bloomberg and Refinitiv Eikon, which holds for stock and CDS indices.[42] Limiting the European sample to the Eurozone ensures that the ECB's policy has a direct impact. The CDSs are written on senior unsecured debt with a term of five years and the end-of-day mid-spread is selected. With regard to stocks, we use daily closing prices.

Only stocks that meet both of the following criteria are considered to generate sufficiently representative and reliable samples: (1) returns must be available every day within the event window, and (2) the combined number of missing observations and zero returns must not exceed 50% of the estimation window. CDS spread changes are only considered if (1) they are available each day in the event window and (2) and missing observations do not exceed 50% of the estimation window.[43] The inclusion criterion for CDS spread changes is less strict than for returns because zero changes in CDS spreads are not problematic in the estimation window. While a zero change in stock returns suggests that the stock price remained unchanged due to nontrading, CDS spreads are

[42] It is also possible to use bonds to capture the impact on debt. However, using CDS spreads is advantageous for various reasons, e.g., Longstaff et al. (2005); Bessembinder et al. (2009); Ericsson et al. (2009); Andres et al. (2021).

[43] We calculate returns and CDS spread changes as logarithmic differences of the stock prices and CDS spreads, respectively.

only available on days with a newly concluded contract. Thus, a zero change in CDS spreads does not indicate a lack of trading but that the perceived risk has remained unchanged from the creditor's perspective. Applying liquidity criteria ensures that central bank information is incorporated into market prices, thereby rendering it observable and quantifiable. The criteria are applied separately to the different event windows (as explained in the next section) in order to maximize the portfolio size of bank and insurer stocks as well as CDSs in each case. Insolvent and nationalized firms are excluded afterwards.

3.4.2 Estimating Abnormal Returns and CDS Spread Changes

Abnormal returns $AR_{i,t}$ of firm i at time t are calculated as prediction errors using the market model of Sharpe (1963) in line with the methodological literature, e.g., Brown and Warner (1985); MacKinlay (1997).[44] We compute them as follows

$$AR_{i,t} = R_{i,t} - (\hat{\alpha}_i^r + \hat{\beta}_{1,i}^r R_{m,t}), \tag{13}$$

where $R_{i,t}$ and $R_{m,t}$ are the actual return of firm i at time t and the return of a market index, respectively. The subtrahend represents the expected returns, estimated using OLS with parameters derived from the estimation window. The choice of a stock index can significantly influence the results. Supranational and broad indices are less prone to bias than national indices, as they mitigate the correlation between financial and nonfinancial firms within a single country and the correlation among financial firms across different countries (Ongena et al., 2003). Thus, the effect of interest rate hikes should be less pronounced, as the influence of financial firms is diminished due to greater diversification and a larger number of constituents. Consequently, the abnormal effect of central bank interest rate hikes can be identified in a more isolated manner. Therefore, stock market reactions are computed using the MSCI World.

In contrast, evidence suggests that various factors, primarily macroeconomic factors (Collin-Dufresne et al., 2001; Ericsson et al., 2009), contribute to explaining CDS spreads. Therefore, following Couaillier and Henricot (2023), we utilize the factor model proposed by Andres et al. (2021) to estimate abnormal CDS spread changes $\Delta AS_{i,t}$ for firm i at time t within the event window

$$\Delta AS_{i,t} = \Delta S_{i,t} - (\hat{\alpha}_i^s + \hat{\beta}_{1,i}^s \Delta S_{index,t} + \hat{\beta}_{2,i}^s Level_t + \hat{\beta}_{3,i}^s Slope_t + \hat{\beta}_{4,i}^s \Delta Vola_t). \tag{14}$$

The actual CDS spread change of firm i at time t is $\Delta S_{i,t}$. The expected CDS spread changes of firm i at time t are reflected by the subtrahend, with parameters estimated in the estimation window using OLS. The change in the CDS market index is $\Delta S_{index,t}$. Because no global CDS index exists,

[44] No multifactor model is used as additional factors provide only marginally more explanatory power (MacKinlay, 1997).

the iTraxx Europe 5-years is utilized for the European CDS market, and the iTraxx CDX IG 5-years is utilized for the U.S. CDS market. The risk-free interest rate level is represented by $Level_t$, which is proxied by the 5-year interest rate swap rate referenced to the 3M EURIBOR in Europe and the 3M LIBOR in the U.S. The slope of the risk-free interest rate, denoted as $Slope_t$, is measured as the difference between the 10-year and 1-year swap rates, following the same specifications for Europe and the U.S. The daily change in equity-implied volatility, denoted as $\Delta Vola_t$, is proxied by the VSTOXX for Europe and the VIX for the U.S., respectively.

Because events over nearly two years are investigated, estimated parameters are unlikely to be stable over time and therefore a separate estimation window is constructed for each event. There is a trade-off in the choice of an appropriate estimation window because as the period increases, the accuracy of the model parameters increases while also increasing the probability that these same parameters have changed and overlapping events occur. Given that events are simultaneous to the Russia-Ukraine affair with far-reaching macroeconomic implications, a 150-day estimation window prior to each event window is used to strike a reasonable balance of statistical accuracy and to avoid bias in the estimated coefficients due to confounding events. For each event, various event windows are examined, with the respective estimation period being identical and ending ten trading days before the event day.

Direct bias in the calculation of the prediction error is a greater concern when confounding events occur within the event window. Thus, we utilize short event windows in line with prior research (Moenninghoff et al., 2015; Fiordelisi and Ricci, 2016; Carboni et al., 2017; Bruno et al., 2018), because this problem increases with a larger event window.[45] We analyze a 3-day $(-1; 1)$ event period and the following sub-periods: 2-day $(-1; 0)$, 2-day $(0; +1)$ and 1-day $(0; 0)$. In the event window (t_1, t_2)[46], the corresponding cumulative abnormal returns $CAR_i(t_1, t_2)$and cumulative abnormal CDS spread changes $\Delta CAS_i(t_1, t_2)$ are calculated for each firm i as follows

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{i,t}, \tag{15}$$

$$\Delta CAS_i(t_1, t_2) = \sum_{t=t_1}^{t_2} \Delta AS_{i,t}. \tag{16}$$

For each event, we compute average cumulative abnormal returns $\overline{CAR}(t_1, t_2)$ and CDS spread

[45]Using a short event window with daily data raises the power of the significance tests so that the probability of a type II error is reduced (Schäfer et al., 2016). A type II error implies that the null hypothesis of no capital market reaction cannot be rejected, although the effect actually differs from zero.

[46]This notation generically refers to the event window from t_1 to t_2, without implying specific relative days like t_{+1} or t_{+2}.

changes $\overline{\Delta CAS}(t_1, t_2)$ for portfolios of N firms

$$\overline{CAR}(t_1, t_2) = \frac{1}{N} \sum_{i=1}^{N} CAR_i(t_1, t_2), \tag{17}$$

$$\overline{\Delta CAS}(t_1, t_2) = \frac{1}{N} \sum_{i=1}^{N} \Delta CAS_i(t_1, t_2). \tag{18}$$

3.4.3 Significance Tests

In a next step, we test whether $\overline{CAR}(t_1, t_2)$ and $\overline{\Delta CAS}(t_1, t_2)$ are significantly different from zero.[47] Regarding the test specification, a distinction can be made between parametric and nonparametric tests, with parametric tests requiring normality of abnormal returns while nonparametric tests are not based on distributional assumptions. As noted in the literature (e.g., Brown and Warner (1985)), an event-induced increase in the variance of $AR_{i,t}$ during the event window relative to the estimation period can lead to an overrejection of the null hypothesis. Hence, we use the standardized cross-sectional parametric test proposed by Boehmer et al. (1991) that considers an event-induced volatility increase, as it is done in previous studies (Fiordelisi et al., 2014; Ricci, 2015; Carboni et al., 2017). In a first step, the standardization factor $SR_{i,t}$ of firm i at time t is calculated as follows

$$SR_{i,t} = \frac{CAR_i(t_1, t_2)}{\hat{\sigma}_{\epsilon_i} \sqrt{T_s + \frac{T_s^2}{T} + \frac{\sum_{t=t_1}^{t_2} (R_{m,t} - T_s(\overline{R}_m))^2}{\sum_{t=1}^{T} (R_{m,t} - \overline{R}_m)^2}}}, \tag{19}$$

where $CAR_i(t_1, t_2)$ is the cumulative abnormal return of firm i in the event window (t_1, t_2). The denominator reflects the standard deviation of $CAR_i(t_1, t_2)$ and consists of two parts, where $\hat{\sigma}_{\epsilon_i}$ denotes the residual standard deviation of the estimation period regression of firm i, while the root term results from the fact that abnormal returns represent an out-of-sample prediction (Campbell et al., 1997).[48] The number of days in the event and estimation windows are represented by T_s and T, respectively. The return of the market portfolio in t is denoted by $R_{m,t}$ and $\overline{R}_m$ is the average market portfolio return in the estimation window. We compute the Z statistic as follows (Mikkelson

[47]For the sake of brevity, the test statistics are only explained using the $\overline{CAR}(t_1, t_2)$. Only if the test procedure for $\overline{\Delta CAS}(t_1, t_2)$ deviates, it will be addressed.

[48]The standardization works statistically analogously for the $\overline{\Delta CAS}(t_1, t_2)$, which are estimated with a multi-factor model. E describes the calculation of the variance in detail.

and Partch, 1988; Mentz and Schiereck, 2008)

$$Z = \frac{\frac{1}{N}\sum_{i=1}^{N} SR_{i,t}}{\sqrt{\frac{1}{N(N-1)}\sum_{i=1}^{N}(SR_{i,t} - \sum_{i=1}^{N}\frac{SR_{i,t}}{N})^2}}, \tag{20}$$

where N is again the number of portfolio firms. The Z statistic is student distributed with $T-2$ degrees of freedom.[49] However, the presented test procedure is not robust against cross-sectional correlation of abnormal returns, which results from event-date clustering and the fact that we consider one sector (banks and insurers are analyzed separately). Kolari and Pynnönen (2010) provide evidence that even relatively low cross-correlation is serious in terms of overrejecting the null hypothesis and that multiplying the Z statistic with the following adjustment factor

$$\sqrt{\frac{1-\overline{r}}{1+(N-1)\overline{r}}} \tag{21}$$

yields a robust test statistic, where $\overline{r}$ is the average of pairwise cross-sectional correlations of the regression residuals in the estimation period.

Although the Z statistic converges to normal distribution, the nonparametric rank test of Corrado and Zivney (1992) is additionally used, because Kolari and Pynnönen (2010) show that this test shares the robustness and power properties of the adjusted Z statistic for small event windows.[50] Additionally, Andres et al. (2021) demonstrate that this test performs particularly well with CDS data. To yield standardized abnormal returns $SAR_{i,t}$, the estimation period $AR_{i,t}$ are standardized by the estimated residual standard deviation, while the event period $AR_{i,t}$ are standardized by their estimated standard deviation that incorporates additional variance due to the sampling error in the estimated parameters.[51] To account for an event-induced volatility increase, the following cross-sectional variance adjustment is performed on each day in the event window

$$X_{i,t} = \begin{cases} SAR_{i,t} & t \notin \{t_1, .., t_2\} \\ SAR_{i,t}/S(SAR_t) & t \in \{t_1, .., t_2\}, \end{cases} \tag{22}$$

where $S(SAR_t)$ is the day t cross-sectional standard deviation. Then, each time series of $X_{i,t}$ is ranked, taking into account both the estimation and event window, implying $T_s + T$ ranks for each

[49]Testing $\overline{\Delta CAS}(t_1, t_2)$ involves $T-5$ degrees of freedom.

[50]This test is a modification of the rank test proposed by Corrado (1989) in that it makes an adjustment for potential missing returns and a cross-sectional variance adjustment is implemented.

[51]In contrast to the original paper, abnormal returns during the event period are standardized using the standard deviation to account for their nature as prediction errors.

firm i. Calculated ranks are standardized as follows to allow for missing values

$$U_{i,t} = \frac{\text{rank}(X_{i,t})}{(1 + Q_i)}, \tag{23}$$

where Q_i denotes the number of nonmissing returns in each time series for firm i. This results in a uniform distribution with an expected value of 0.5. It leads to the following test statistic

$$Z_c = \frac{\sum_{t=t_1}^{t_2} \frac{1}{\sqrt{N}} \sum_{i=1}^{N} (U_{i,t} - 0.5)}{\sqrt{T_s} S(U)}, \tag{24}$$

where the numerator corresponds to the average cumulative rank in the event window (t_1, t_2) (Campbell and Wesley, 1993). The standard deviation $S(U)$ is calculated over the entire sample period

$$S(U) = \sqrt{\frac{1}{T + T_s} \sum_{t=-159}^{t_2} (\frac{1}{\sqrt{N_t}} \sum_{i=1}^{N_t} (U_{i,t} - 0.5))^2}, \tag{25}$$

where N_t denotes the number of nonmissing returns in the cross-section of N firms for each t.[52] The denominator is adjusted with the square-root-of-time rule and the test statistic converges to standard normal.

3.4.4 Measuring Monetary Shocks

As explained, markets incorporate anticipated changes, implying that only the unexpected component of monetary policy affects asset valuation. Consequently, central banks can also shock markets through inaction, i.e. when markets were expecting the central bank to act (Swanson, 2021). While we examine central bank rate hikes in this paper, it is important to note that monetary policy has more than one dimension—the change in the policy rate itself—that can affect markets. This is explained below together with the method of isolating monetary policy surprises for both the Eurozone and the U.S.

We use the EA-MPD and the corresponding framework of Altavilla et al. (2019) to calculate Eurozone's monetary policy suprises. The EA-MPD contains high-frequency interest rate changes in the press release and press conference window, measured as the change in median prices within 10-minute intervals before and after these events. An ECB decision is announced in two separate steps, namely a press release at 1:45 pm Central European Time (CET) decribing the decision briefly without any explanation and comments, followed by the Introductory Statement (IS) at 2:30 pm

[52]The entire sample period comprises the 150 days of the estimation window as well as the days of the event window between (t_1, t_2). Recall that the estimation window ends ten trading days prior to the event day t_0.

CET, in which the rationale behind the decision is explained. This second step is accompanied by a subsequent question-and-answer session informing markets about the future path of monetary policy.

The methodology of Altavilla et al. (2019) is based on Gürkaynak et al. (2005) and Swanson (2021). The $T_p \times n_{hf}$ matrix X^j, $j = \{\textit{press release, press conference}\}$, contains seven columns of high-frequency changes in overnight index swaps (OISs) with maturities of one, three, and six months, and one, two, five, and ten years, while each row corresponds to a policy date. We apply principal component analysis (PCA) to estimate the following factor structure separately for the press release and press conference windows

$$X^j = F^j \Lambda^j + \epsilon^j, \tag{26}$$

where F^j is a $T_p \times k_{lf}$ matrix containing $k_{lf} \leq n_{hf}$ latent factors, Λ^j is a $k_{lf} \times n_{hf}$ matrix of factor loadings, and ϵ^j is a $T_p \times n_{hf}$ matrix of idiosyncratic variations. We extract the first principal component for the press release window and the first three principal components for the press conference window. The following rotation allows an economic interpretation of these factors (see Gürkaynak et al. (2005); Altavilla et al. (2019); Swanson (2021) for details). As they load on different maturities, following Altavilla et al. (2019), the press release factor is labeled $target^E$, while the three factors of the press conference window are labeled *timing*, forward guidance (*FG*) and quantitative easing (*QE*), respectively.[53] The factors are scaled such that $target^E$ has unit effect on the one-month OIS, *timing* has unit effect on six-month OIS, *FG* has unit effect on two-year OIS and *QE* has unit effect on ten-year OIS. Hence, positive factors indicate contractionary monetary policy. The $target^E$ factor of the press release window captures the surprise component related to the decisions on setting interest rates and reflects conventional monetary policy. This is intuitive because the press release only contains the interest rate decision. The factors emerging from the press conference pertain to the future path of interest rates and QE, distinguishing them from the $target^E$ factor which is relevant only to short-term interest rates. The factors of the future path are *timing* and *FG*. *Timing* captures revisions in interest rate expectations for upcoming ECB meetings, with its influence peaking at a maturity of six months. In contrast, the *FG* factor shapes medium-term interest rate expectations and peaks at a maturity of two years. FG is a component of the ECB's unconventional monetary policy, a characterization that also applies to QE, the third factor in the press conference window. QE refers to the purchase of government bonds and other assets aimed at lowering long-term interest rates. The *QE* factor differs from the *FG* factor in that it affects long-term interest rates, peaking at a maturity of ten years. Due to the orthogonal construction of the three press conference window factors, they can be summed up to show the overall effect of this

[53] Superscripts E and F denote ECB and Fed announcements, respectively. A *target* factor also appears in the Fed context, so the superscripts serve to distinguish between otherwise similarly named factors.

window (Baumgärtner, 2020). This factor is called *path_conf* to distinguish it from the *path* factor of Fed policy, as described in the following.

The method of estimating the surprise element of Fed announcements follows Gürkaynak et al. (2005) and works similar to the aforementioned one.[54] The FOMC's decision is announced and explained in a single press release. Unlike the ECB's decision process, this provides only one observation window for the calculation of monetary policy shocks. Changes in the following asset prices are collected within a 30-minute window surrounding each FOMC event (ten minutes before and 20 minutes after): federal funds futures (current-month and three-month-ahead contract rates), and Eurodollar futures (two-, three-, and four-quarter-ahead contracts). Starting in January 2023, due to their discontinuation, Eurodollar futures are replaced by Secured Overnight Financing Rate (SOFR) futures (Acosta et al., 2024). The federal funds futures contracts are scaled by the number of days remaining in the month to provide the best estimate of the suprise component in the federal funds rate (Kuttner, 2001). Similar to X^j, starting point is a matrix with five columns of asset price changes where each row corresponds to one FOMC event. Analogous to Eq. (26), a factor structure is used to detect monetary shocks; the difference is that a single observation window exists, rendering the superscript j obsolete. Two factors are extracted using principal components and subsequently labeled, after appropriate rotation, as $target^F$ and *path* factors.[55] The $target^F$ factor is calibrated to correspond directly to a one-to-one change in the current month's federal funds futures. Similarly, the *path* factor is scaled to align one-to-one with the change in the fourth outstanding eurodollar futures/fifth outstanding SOFR futures. Analogously, positive factors correspond to a contractionary monetary policy. Although we focus on interest rate hikes, both expansionary (negative factors) and contractionary (positive factors) shocks can occur. This fundamentally depends on market expectations. For instance, an interest rate increase may turn out to be smaller than anticipated (e.g., 50 bps instead of the expected 75 bps), which would constitute an expansionary shock. The factors of the ECB's and Fed's monetary policy surprises are displayed in F.[56]

3.4.5 Cross-Sectional Analysis

In the next step, we investigate the extent to which CARs and ΔCAS are driven by the identified monetary policy shocks. This enables a more detailed analysis of how conventional and unconventional monetary policy measures affect shareholders and creditors, and whether these effects differ between banks and insurers. To this end, we estimate separate OLS regressions with clustered standard errors for banks and insurers, and for the U.S. and the Eurozone, regressing $CAR_i(t_1,t_2)$ and $\Delta CAS_i(t_1,t_2)$ on the respective monetary policy factors, as specified in Eq. (27)–Eq. (30) for

[54] We cannot calculate the three factors from Swanson (2021) because we do not have the data.

[55] We use the factors provided by Acosta et al. (2024) because we do not have the data to perform the calculations ourselves.

[56] Due to data availability of the EA-MPD, we are only able to compute shocks up to October 26, 2023.

ECB and Fed announcements, respectively

$$CAR_i(t_1, t_2) = \alpha^{E,r} + \beta_1^{E,r} target_t^E + \beta_2^{E,r} timing_t + \beta_3^{E,r} FG_t + \beta_4^{E,r} QE_t + \epsilon_{i,t}^{E,r}, \tag{27}$$

$$\Delta CAS_i(t_1, t_2) = \alpha^{E,s} + \beta_1^{E,s} target_t^E + \beta_2^{E,s} timing_t + \beta_3^{E,s} FG_t + \beta_4^{E,s} QE_t + \epsilon_{i,t}^{E,s}, \tag{28}$$

$$CAR_i(t_1, t_2) = \alpha^{F,r} + \beta_1^{F,r} target_t^F + \beta_2^{F,r} path_t + \epsilon_{i,t}^{F,r}, \tag{29}$$

$$\Delta CAS_i(t_1, t_2) = \alpha^{F,s} + \beta_1^{F,s} target_t^F + \beta_2^{F,s} path_t + \epsilon_{i,t}^{F,s}. \tag{30}$$

For the insurer subsample, an additional dummy variable LIFE_i is included, which equals 1 for life insurers and 0 otherwise.

3.5 Results

3.5.1 Market Reactions

3.5.1.1 Fed

The event study results are presented in Tabs. 9 to 12. Analogous to Ricci (2015), we find the significance of $\overline{CAR}$ and $\overline{\Delta CAS}$ for the test of Boehmer et al. (1991) decreasing significantly due to correction for cross-sectional correlation.[57] In general, we observe significant $\overline{CAR}$ and $\overline{\Delta CAS}$, especially in instances of pronounced monetary shocks. This is consistent with theoretical expectations, suggesting that markets primarily respond to the unexpected component of monetary policy. More specifically, our findings demonstrate that shareholders react significantly to various Fed and ECB announcements. This aligns with prior research on the effects of monetary policy on stock prices, which mainly focuses on indices such as the S&P 500 or the STOXX50E. In contrast, we direct our analysis toward banks and insurers, assessing the significance of individual events. Additionally, we contribute to the literature by incorporating CDSs, revealing that creditors perceive substantial shifts in risk profiles of financial intermediaries. Furthermore, our study highlights significant spillover effects, showing that shareholders and creditors of U.S. financial intermediaries react to ECB monetary policy, and vice versa. These findings emphasize the global interconnectedness of financial markets, capital flows, and macroeconomic dynamics. In addition to this general interpretation of the results, we discuss them within the framework of theoretical considerations. Specifically, we analyze how shareholders and creditors respond to monetary policy shocks and identify the key drivers behind these reactions. The presence of spillover effects makes it particularly interesting to assess whether domestic and foreign market reactions align in both direction and magnitude.

After the abstract classification of the results, we now proceed with a more detailed contextualization, starting with the Fed events. Of particular importance for U.S. bank shareholders are December 14, 2022, March 22, 2023, and May 3, 2023, leading to negative and significant $\overline{CAR}$.

[57] The results of the uncorrected test are untabulated.

For the first event, positive realizations of the $target^F$ and especially the *path* factor of 0.197 indicate contractionary shocks. The second event shows the largest realization of the $target^F$ factor of 0.059 during our observation period, while the *path* factor is negative with -0.21. It is likely that the contractionary conventional monetary shock dominates, particularly because its magnitude is significantly larger. The most negative $\overline{CAR}$ occurred during the last mentioned event in the (-1;+1) window, with -0.072 ($*|**$), indicating a portfolio value drop of 7.2%. In this context, we observe distinct positive $target^F$ and *path* factors with values of 0.023 and 0.025, respectively, indicating contractionary shocks. Positive $\overline{CAR}$ are documented on December 13, 2023, with values up to 0.054 ($*|**$) in the (0;+1) window. This coincides with the most negative realization of the *path* factor, suggesting that markets anticipate a future shift away from contractionary monetary policy. The simultaneously occurring $target^F$ factor is negligible, with a value of 0.017. Among the previously mentioned events, March 22, 2023, is relevant for U.S. insurer shareholders as well, who similarly exhibit negative $\overline{CAR}$. The largest absolute reaction is observed in the (0;+1) window, with -0.035 ($**|***$). Additionally, June 14, 2023, is significant, as negative stock reactions are observed, e.g. -0.019 ($**|**$) in (0;0). Here, we see a negligible $target^F$ factor of -0.014, while the *path* factor of 0.262 indicates a contractionary shock.

Similar to stocks, March 22, 2023, is particularly relevant for U.S. creditors, with negative $\overline{\Delta CAS}$ reaching -0.099 ($***|**$) in (-1;0) for banks and -0.045 ($**|**$) in (0;0) for insurers. Again, this marks the event with the largest realization of the $target^F$ factor of 0.059 and a negative realization of the *path* factor of -0.21. Other significant dates include November 2, 2022, where creditors of both banks and insurers respond with significantly negative $\overline{\Delta CAS}$. At this event, both the $target^F$ and *path* factors are negative, with values of -0.01 and -0.145, respectively. The event on December 13, 2023, is also notable, with the most negative values for banks observed in (-1;+1) at -0.062 ($**|***$) and for insurers in (0;+1) at -0.065 ($**|***$). This event features the most negative *path* factor at -0.238, while the $target^F$ factor remains near zero.

There are also events in which either only the creditors of banks or those of insurers respond. Banks exhibit significant negative $\overline{\Delta CAS}$ on March 16, 2022, and September 20, 2023. For the former event, we observe a negative $target^F$ factor of -0.027 and a positive, i.e., contractionary, *path* factor of 0.304. For the latter event, the $target^F$ factor is close to zero, while the *path* factor of 0.191 indicates contractionary monetary policy. We observe significantly negative $\overline{\Delta CAS}$ for insurers on January 26, 2022, and November 1, 2023. As previously discussed, no substantial monetary shocks are detected for the former event. For the latter event, the $target^F$ and *path* factors are negative but minor, with values of -0.005 and -0.012, respectively.

Overall, we observe a clear pattern among U.S. bank and insurer shareholders. Contractionary shocks (i.e., positive $target^F$ and *path* factors) lead to negative $\overline{CAR}$, and vice versa. From a shareholder perspective, unexpected rate hikes and corresponding outlooks reduce profitability. Theoretically, an increase in the discount rate exerts downward pressure on stock prices while enhancing the attractiveness of fixed-income securities. This is because newly issued bonds offer higher yields, making them more appealing relative to stocks. Consequently, investors reallocate capital from stocks to bonds as the improved risk–return profile of fixed-income securities becomes more favorable. However, existing bonds decline in market value due to the higher discount factor. The extent of this capital reallocation depends on broader market conditions and investor expectations regarding future monetary policy and economic growth. This aligns with the textbook transmission mechanism of a monetary policy shock and confirms previous findings on the effects of Fed policy on U.S. stocks (e.g. Bernanke and Kuttner, 2005; Gürkaynak et al., 2005; Swanson, 2021).

The assignment of monetary policy shocks to CDS market reactions tends to be less clear-cut. When considering all significant events, in the majority of cases, expansionary shocks lead to decreasing CDS spreads and vice versa. For the events in which we observe significant reactions from both banks and insurers—namely on November 2, 2022, March 22, 2022, and December 13, 2023—the direction of the effect is identical. From the creditors' perspective, the risk associated with U.S. banks and insurers evolves in a comparable manner. Declining CDS spreads in response to expansionary shocks (i.e., negative $target^F$ and *path* factors) suggest that U.S. creditors perceive lower risk, whereas contractionary shocks are associated with higher perceived risk. As discussed in Sec. 3.3.2, there are several theoretical explanations for rising CDS spreads in response to contractionary monetary policy. It is important to note that our CDS portfolios predominantly include large banks, which are naturally more engaged in proprietary trading. In this context, trading losses may arise as an initial channel. Furthermore, we have discussed how declining credit quality and a reduction in credit supply can adversely affect banks, as both may reduce net interest income and, in turn, increase the PD. Insurers' CDS spreads behave similarly to those of banks. From the perspective of insurance creditors, the negative effects of the interest rate hikes on asset valuation are dominant. In particular, insurers hold bonds whose market values decline with rising interest rates, leading to impairments. This reduces equity, thereby increasing the PD. Moreover, insurers also hold stocks, which—as we have shown—decrease in value as well.

The first analyzed event on January 26, 2022, is particularly relevant for Eurozone bank and insurer shareholders, as it shows positively significant $\overline{CAR}$. The largest reactions are measured in the (-1;+1) window, with values of 0.046 (∗∗|∗∗∗) for banks and 0.048 (∗∗∗|∗∗∗) for insurers. The Fed left interest rates unchanged and the $target^F$ and *path* factors, at -0.002 and 0.0002, respectively, are not pronounced. This example illustrates that market movements cannot always be explained by monetary shocks. As described by Swanson (2021), stocks (and also CDSs) exhibit significantly higher idiosyncratic volatility compared to, for example, Treasuries. Additionally, market reactions are measured in windows of up to three days, whereas the Fed's monetary shocks are calculated in 30-minute windows around the interest rate decision, which increases the risk of confounding events.

Positive $\overline{CAR}$ are also observed on November 2, 2022, whereby negative $target^F$ and *path* factors of -0.01 and -0.145 emerge. In the (-1;+1) window, values of 0.027 ($*|**$) for banks and 0.02 ($|**$) for insurers emerge. Significant negative values appear on March 22, 2023, in the (0;+1) window for banks and insurers, while shareholders of the latter exhibit a positive reaction in the (-1;0) window. This event is associated with a contractionary $target^F$ factor of 0.059 and an expansionary *path* factor of -0.21. Furthermore, for banks, September 20, 2023, is of particular importance due to positive $\overline{CAR}$. Although the $target^F$ factor is rather weak at -0.004, the *path* factor of 0.191 indicates a contractionary shock. Another notable event is the final Fed decision on December 13, 2023, resulting in negative $\overline{CAR}$ for Eurozone institutions, contrasting with the positive reactions of U.S. banks. This event is characterized by the most negative *path* factor. However, the negative Eurozone reactions might not reflect the Fed event on December 13, 2023, but rather the ECB decision on December 14, 2023.

The reactions of creditors of Eurozone intermediaries to Fed events are less pronounced. Both bank and insurance portfolios exhibit positive $\overline{\Delta CAS}$ on September 21, 2022. The most negative value of the $target^F$ factor is observed at -0.037, while the *path* factor is distinctly positive at 0.299. For banks, values of 0.034 ($|*$) are evident in the (-1;+1) window, whereas for insurers, values of 0.045 ($*|$) are observed in the (-1;0) window. Another significant event is June 14, 2023, where creditors of banks and insurers experience positively significant $\overline{\Delta CAS}$. The *path* factor of 0.262 indicates a contractionary shock, while the $target^F$ factor remains close to zero.

Overall, we find significant spillover effects of the Fed's policy on Eurozone financial intermediaries, which is consistent with previous research (Ehrmann and Fratzscher, 2004; Ammer et al., 2010; Laeven and Tong, 2012). Starting with stocks, we observe that both the direction and magnitude of the effects are consistent across events where banks and insurers react jointly—specifically on January 26, 2022; May 4, 2022; November 2, 2022; and within the (0;+1) event window on March 22, 2023, and December 13, 2023. Thus, there initially appears to be no particularly different perspective on the impact of the Fed's monetary policy on return expectations between Eurozone banks and insurers. If we assume that the $target^F$ and *path* factors have an equal-weighted impact on stock markets, and that the classification of an event as expansionary or contractionary depends on the factor with the greater absolute magnitude when the signs of the factors differ, then a pattern emerges between significant $\overline{CAR}$ and the monetary shocks. Excluding the first and last event (due to ECB overlap), contractionary shocks are met with positive reactions, while expansionary shocks lead to negative responses. This pattern contrasts with the responses of U.S. shareholders. It can be argued that positive and negative Fed monetary shocks affect the expected return of U.S. shareholders through the discount factor, reducing or increasing it, respectively. This, in turn, triggers capital flows between the U.S. and Eurozone stock markets. Ceteris paribus, positive Fed shocks make Eurozone stocks more attractive, and vice versa.

Spillover effects are also evident in credit markets. We observe that the direction and magnitude of effects are consistent for events that exhibit significant $\overline{\Delta CAS}$ for both banks and insurers, such as on September 21, 2022, and June 14, 2023. This suggests that, from a creditor's perspective, the risk associated with banks and insurers changes in a similar manner. Considering all significant CDS market reactions, a similar pattern to U.S. creditors emerges. Contractionary shocks drive CDS spreads higher, while expansionary shocks cause them to decline. A similar reaction pattern of U.S. and Eurozone creditors may be explained by the composition of the CDS portfolios, which include only large institutions. These typically operate across borders and are therefore more sensitive to foreign interest rate changes than smaller, local institutions.

3.5.1.2 ECB

We now turn to the ECB events. For U.S. insurers, of importance is July 21, 2022, with negative $\overline{CAR}$. In this context, values of -0.017 (∗|∗∗) and -0.02 (|∗) appear in the (-1;+1) and (0;+1) windows, respectively. We observe a positive $target^E$ factor of 3.691, indicating a conventional contractionary shock. In contrast, the press conference window reveals a particularly pronounced negative *QE* shock of -7.523. Economically, this implies that the announcement led markets to experience an unexpected decrease in long-term interest rates. On October 27, 2022, positive $\overline{CAR}$ of 0.028 (|∗) and 0.023 (∗|∗∗) show up in the same event windows. The $target^E$ factor of 2.616 indicates a contractionary shock, whereas, in particular, the *QE* factor of the press conference window with -3.687 implies again that markets perceive an unexpected decrease in long-term interest rates. For U.S. banks, significant and positive $\overline{CAR}$ are observed for the first time on February 2, 2023, with values of 0.02 (∗|∗) and 0.019 (∗∗|∗∗) in the event windows (-1;+1) and (0;+1), respectively. The $target^E$ factor in the press release window at 0.548 is relatively subdued. The three factors of the press conference window are negative and sum up to a *path_conf* factor of -4.089.

Furthermore, on March 16, 2023, negative $\overline{CAR}$ can be observed for insurers, for instance, with a value of -0.038 (∗∗|∗) in (-1;+1). The bank reaction is less pronounced. Only in the (0;0) window, a slightly significant value of 0.018 (|∗) is recorded. In this context, the largest $target^E$ factor of 21.12 is observed, along with similarly positive *FG* and *QE* factors of 6.825 and 3.66, respectively, resulting in a cumulative *path_conf* factor of 9.544. On October 26, 2023, positive reactions from bank shareholders with values of 0.056 (∗|∗∗) and 0.039 (∗|∗∗) are observed in the (-1;0) and (0;0) windows, respectively. Similarly, insurers exhibit a slightly significant positive value of 0.02 (|∗). The negative $target^E$ factor and the overall negative *path_conf* factor of -3.455 suggest an expansionary shock. The positive reactions for banks and the negative reactions for insurers on December 14, 2023, are likely attributable to the Fed event that took place the day before.

Regarding U.S. creditors, we predominantly observe significant $\overline{\Delta CAS}$ for banks. On June 9, 2022, the most negative value in (-1;0) is -0.024 (∗∗∗|∗∗). In the same window, insurers exhibit a negative and at least slightly significant value of -0.015 (|∗). Negative press release and press conference factors can be observed. For banks, during the subsequent event on July 21, 2022, the portfolio exhibits distinctly negative and consistently significant reactions across all windows, with the largest value of -0.055 (∗∗∗|∗∗∗) in (-1;+1). A positive $target^E$ factor of 3.691 is observed. Notably, the *QE* factor reaches its most negative value of -7.523 during our observation period. For banks, negative $\overline{\Delta CAS}$ are also evident on October 27, 2022. For the first time, positive reactions can be observed on March 16, 2023, where the largest value in (-1;+1) is 0.241 (|∗) for the bank portfolio. Similarly, we observe positive $\overline{\Delta CAS}$ for U.S. insurers as well, with the largest value in (-1;0) being 0.062 (∗∗|∗∗). During this event, the $target^E$ factor records by far the largest shock at 21.12, with the *FG* and *QE* factors also showing pronounced values of 6.825 and 3.66, respectively. Other notable events include October 26, 2023, and December 14, 2023, with significantly negative $\overline{\Delta CAS}$ across all windows for banks. Insurers also respond with highly significant negative $\overline{\Delta CAS}$ across all windows for the latter event, e.g. with a value of -0.077 (∗∗|∗∗∗) in (-1;+1). For the former event, negative press release and press conference windows are evident, while for the latter event, the factors cannot be calculated due to the lack of data availability in the EA-MPD. However, these reactions are likely attributed to the Fed event the day before, where especially the *path* factor shows the most negative value of -0.238 in our sample.

We provide evidence for spillover effects of ECB policy on U.S. shareholders, but no clear reaction pattern can be identified. In contrast to the reactions of Eurozone intermediaries to the Fed events, for events where both insurers and banks respond significantly, the magnitude and direction of effects do not consistently align. One reason for the ambiguity in stock market reactions could be the fact that in the U.S. many smaller financial intermediaries, such as small regional banks, are publicly listed, and are thus included in the portfolio under consideration, although they are not affected by ECB decisions. In contrast to large banks, they do not operate in the Eurozone, but rather engage in traditional commercial banking with a local focus and without significant proprietary trading in international financial markets.

Overall, we observe that U.S. creditors also respond, with bank reactions being more pronounced. This is likely due to the fact that the U.S. bank CDS sample includes only major banks. Their higher responsiveness can be attributed to their interconnectedness within the international financial system. Overall, it appears that expansionary shocks lead to declining CDS spreads, and vice versa. This effect can be explained through spillover mechanisms: an expansionary shock, in which ECB policy is less restrictive than expected, results in a more moderate tightening of financing conditions in Europe. This indirectly affects the refinancing conditions of internationally active U.S. banks with strong ties to the Eurozone market. Once again, arguments can be made here regarding trading losses, a deterioration in credit quality, and a contraction in credit supply. From the viewpoint of insurance creditors, the dominant factor is the impairment effect, which is primarily attributable to fixed-income securities.

Regarding Eurozone reactions, March 16, 2023, is of great importance for shareholders. For banks, significantly negative stock reactions are observed, with the largest value of -0.074 (∗∗∗|∗∗∗) in the (-1;+1) window. This implies a loss of 7.4% for the bank portfolio. Similarly, for insurance portfolios, the largest absolute value is observed in the same window at -0.045 (∗∗∗|∗∗). As already explained, this event is of exceptional importance with the highest $target^E$ and the second-largest *FG* and *QE* factors, implying a distinct contractionary shock. Surprisingly, the stock reaction of banks is only slightly negatively significant on one other occasion, the final event on December 14, 2023. In this context, a $\overline{CAR}$ of -0.015 (|∗) appears in the (-1;0) window. For Eurozone insurance shareholders, this event is also relevant, with negative $\overline{CAR}$ observed across all event windows, e.g. -0.019 (∗|∗) in the (-1;+1) window. Additionally, for insurers, a $\overline{CAR}$ of 0.012 (∗|∗∗) is observed in the (0;0) window on April 14, 2022, and a $\overline{CAR}$ of -0.021 (|∗∗) in the (-1;0) window on July 21, 2022. For the first event, an insignificant $target^E$ factor of -0.568 is observed, along with negative *timing* and *FG* factors of -0.678 and -2.14, respectively. However, the *QE* factor of 5.133 indicates a contractionary shock. As previously discussed, on July 21, 2022, a contractionary $target^E$ factor of 3.691 is present, but the press conference window shows negative factors, particularly an expansionary *QE* shock of -7.523.

Of outstanding importance for the CDS market is also March 16, 2023. Eurozone banks react with distincly significant and positive values across all windows, with the largest being 0.087 (∗|∗∗) in (-1;+1). Similarly, creditors of insurers react in the (0;0) window with a value of 0.073 (∗∗∗|∗∗), indicating an increase in risk perception by 7.3%. This reaction is in line with the reactions of U.S. creditors. Negative significant $\overline{\Delta CAS}$ can be observed for Eurozone banks on October 27, 2022, with the $target^E$ factor being positive with a value of 2.616. However, the *QE* factor is distinct negative with a value of -3.687. Similarly, negative reactions are also evident on October 26, 2023, with negative press release and press conference factors. For insurers, October 27, 2023, is also noteworthy, as CDS spreads increased. The shocks in the press release and press conference windows are negative.

Overall, the ECB event on March 16, 2023, is of paramount importance for Eurozone banks and insurers. It marks both a conventional and an unconventional contractionary shock of outstanding significance. Therefore, this event is a prime example to explain how ECB interest rate policy affects Eurozone markets. We find highly significant negative $\overline{CAR}$ and conversely, positive $\overline{\Delta CAS}$. This extreme contractionary shock reveals that shareholders lower their return expectations, which is in line with a textbook monetary shock. From the perspective of creditors, the contractionary shock leads to an increase in risk. In the banking sector, as discussed, reasons are a deterioration in credit quality, a reduction in credit supply and trading losses. Insurers are likewise impacted, as increases in interest rates adversely affect asset valuations, particularly of fixed-income securities, potentially resulting in realized losses or latent valuation pressures that erode their equity base. This may be amplified by the macroeconomic conditions of high post-COVID inflation rates and Russia's war of aggression against Ukraine, which have generally increased uncertainty and thus risk. The impact of ECB interest rate events on the shareholders and creditors of Eurozone banks and insurers appears to be analogous to that of Fed events on the U.S. markets.

In the initial step of our analysis, we identified the significant market reactions and attempted to contextualize them within the framework of the monetary shocks. To examine this relationship in greater detail, the next section presents the regression results, where firm-level $CAR_i(t_1,t_2)$ and $\Delta CAS_i(t_1,t_2)$ are regressed on the respective shocks to determine their impact. This enables a more precise analysis of which factors genuinely affect abnormal capital market reactions and the magnitude of their influence.

Table 9: U.S. Banks' Market Reactions to Fed and ECB Announcements

	Stock Market: $\overline{CAR}(t_1,t_2)$				CDS Market: $\overline{\Delta CAS}(t_1,t_2)$			
Fed	(-1;0)	(-1;+1)	(0;0)	(0;+1)	(-1;0)	(-1;+1)	(0;0)	(0;+1)
2022-01-26	-0.001	-0.007	-0.009	-0.016	-0.027	-0.017	-0.012	-0.002
	312	310	314	311	9	9	9	9
2022-03-16	-0.012	-0.026 (|*)	-0.001	-0.015	-0.062 (|*)	-0.097 (|***)	-0.045	-0.08 (**|***)
	321	318	322	318	9	9	9	9
2022-05-04	0.008	0.006	0.006	0.003	-0.003	-0.003	0.002	0.002
	320	317	320	317	9	9	9	9
2022-06-15	0.008	0.003	0.002	-0.003	0.004	0.016	0.004	0.016
	324	322	326	323	10	10	10	10
2022-07-27	0.008	-0.002	0.002	-0.008	0.01	0.012	0.011	0.014
	316	312	319	315	10	10	10	10
2022-09-21	0.009	0.003	0.004	-0.002	0.009	0.045 (***|)	-0.003	0.033
	323	323	324	324	10	10	10	10
2022-11-02	-0.001	0.002	-0.002	0.001	-0.035 (**|**)	-0.05 (*|***)	-0.024 (**|**)	-0.039 (**|**)
	320	311	320	311	10	10	10	10
2022-12-14	-0.026 (**|**)	-0.027 (**|*)	-0.013 (|*)	-0.014	-0.003	0.003	-0.013	-0.006
	326	324	330	328	10	10	10	10
2023-02-01	0.014	0.022 (|*)	0.001	0.009	0.007	-0.019	0.003	-0.023
	324	321	329	324	10	10	10	10
2023-03-22	-0.005	-0.028 (*|)	-0.028 (***|***)	-0.051 (***|***)	-0.099 (***|**)	-0.034	-0.084 (**|**)	-0.018
	332	332	333	333	10	10	10	10
2023-05-03	-0.047 (|*)	-0.072 (*|**)	-0.006	-0.031	0.016	0.052 (|*)	0.008	0.044
	340	340	340	340	10	10	10	10
2023-06-14	-0.003	0.006	-0.017 (|*)	-0.008	0.012	0.026 (|**)	-0.006	0.008
	335	334	338	336	10	10	10	10
2023-07-26	0.029	0.029	0.033 (*|**)	0.033	0.005	-0.02	0.005	-0.019
	329	327	333	331	10	10	10	10
2023-09-20	0.003	0.022	0.004	0.022	-0.061 (*|***)	-0.093 (*|***)	-0.04 (|*)	-0.072 (*|***)
	335	330	339	333	10	10	10	10
2023-11-01	-0.018	-0.005	-0.017	-0.003	-0.04	-0.07	-0.018	-0.048
	332	331	337	336	9	9	9	9
2023-12-13	0.024	0.044	0.034 (|*)	0.054 (*|**)	-0.027 (*|**)	-0.062 (**|***)	-0.02 (*|**)	-0.052 (*|***)
	344	343	346	345	9	9	10	10
ECB								
2022-04-14	0	-	-0.002	-	0.014	0.016	-0.004	-0.002
	316	0	318	0	8	8	8	8
2022-06-09	-0.011	-0.012	-0.007	-0.007	-0.024 (***|**)	-0.001	-0.015 (**|*)	0.008
	316	313	316	313	10	10	10	10
2022-07-21	-0.001	-0.003	-0.005	-0.007	-0.03 (**|**)	-0.055 (***|***)	-0.017 (*|*)	-0.042 (***|***)
	312	309	316	310	10	10	10	10
2022-09-08	0.007	0.006	0.003	0.001	0.015	0.014	-0.011	-0.011

	321	319	323	321	10	10	10	10
2022-10-27	0.01	0.022	0.009	0.02	-0.036 (∗∗∗|∗∗∗)	-0.034 (|∗∗)	-0.013	-0.011
	313	310	322	317	10	10	10	10
2022-12-15	-0.014	-0.007	-0.001	0.007	-0.006	-0.003	0.006	0.012
	329	328	333	332	10	9	10	9
2023-02-02	0.009	0.02 (∗|∗)	0.008	0.019 (∗∗|∗∗)	-0.022	-0.043	-0.026	-0.046 (∗|∗∗)
	324	324	328	328	10	10	10	10
2023-03-16	0.019	-0.019	0.018 (|∗)	-0.019	0.191 (|∗)	0.241 (|∗)	0.109	0.158
	333	333	333	333	10	10	10	10
2023-05-04	-0.031	-0.005	-0.025 (|∗)	0.001	0.043	0.023	0.035 (|∗)	0.016
	340	339	341	340	10	10	10	10
2023-06-15	-0.008	-0.008	0.009	0.01	0.008	0.029	0.015	0.036 (|∗)
	336	332	338	334	10	10	10	10
2023-07-27	0.033	0.034	0	0.001	-0.019	-0.019	-0.024 (|∗)	-0.023 (∗∗|)
	330	327	336	333	10	10	10	10
2023-09-14	0	0.008	0.008	0.016	-0.009	-0.027	-0.013	-0.031 (∗|)
	338	338	339	338	10	10	10	10
2023-10-26	0.056 (∗|∗∗)	0.053	0.039 (∗|∗∗)	0.037	-0.052 (∗∗∗|∗∗∗)	-0.047 (∗∗∗|∗∗∗)	-0.038 (|∗)	-0.034 (∗∗|)
	329	326	334	330	5	5	5	5
2023-12-14	0.054 (∗|∗∗)	0.062 (|∗)	0.02	0.027	-0.049 (∗|∗∗∗)	-0.055 (∗|∗∗)	-0.03 (∗|∗)	-0.036 (|∗)
	345	342	345	342	10	10	10	10

This table presents $\overline{CAR}(t_1, t_2)$ and $\overline{\Delta CAS}(t_1, t_2)$ for U.S. banks in response to interest rate decisions by the Fed and the ECB, measured across different event windows. Values are rounded to the third decimal place and calculated according to Eq. (13)–Eq. (18). Statistical significance is assessed using the parametric test of Boehmer et al. (1991), adjusted by Kolari and Pynnönen (2010), and the nonparametric test of Corrado and Zivney (1992). The corresponding p values are based on a two-sided significance test: $^{*}p$<0.1; $^{**}p$<0.05; $^{***}p$<0.01. The first value in parentheses indicates the significance of the parametric test; the second refers to the nonparametric test. The number below each result indicates the portfolio size. The MSCI World Index is used as a proxy for the stock market portfolio, while the iTraxx CDX IG 5-years Index serves as a proxy for the CDS market portfolio.

Table 10: U.S. Insurers' Market Reactions to Fed and ECB Announcements

	Stock Market: $\overline{CAR}(t_1, t_2)$				CDS Market: $\overline{\Delta CAS}(t_1, t_2)$			
Fed	(-1;0)	(-1;+1)	(0;0)	(0;+1)	(-1;0)	(-1;+1)	(0;0)	(0;+1)
2022-01-26	0	-0.009	-0.009	-0.017	-0.029 (|∗∗)	-0.015	-0.022 (∗|∗)	-0.008
	84	84	84	84	25	25	25	25
2022-03-16	-0.002	-0.002	-0.002	-0.002	0.011	-0.013	0.007	-0.017
	84	83	84	83	23	23	24	24
2022-05-04	0.006	0.017	0.003	0.014	0.013	0.029	0.002	0.017
	83	83	83	83	22	22	22	22
2022-06-15	0	-0.012	-0.01	-0.021 (∗|∗)	-0.005	0.016	-0.006	0.015
	82	81	83	82	22	22	22	22
2022-07-27	-0.016	-0.027	-0.013	-0.024 (|∗)	0.019	0.038	0.005	0.024
	82	81	82	81	26	26	26	26
2022-09-21	-0.004	-0.016	-0.01	-0.011	-0.012	0.006	-0.014	0.004
	80	80	81	80	25	25	25	25
2022-11-02	0.003	-0.004	0.001	-0.006	-0.046 (∗∗|∗∗∗)	-0.03 (|∗)	-0.028 (∗∗∗|∗∗∗)	-0.012
	81	81	81	81	26	26	26	26
2022-12-14	-0.008	0.001	-0.003	0.007	-0.025	-0.024 (∗|)	-0.003	-0.002
	79	79	79	79	26	26	26	26
2023-02-01	0.008	0.005	-0.002	-0.005	0.009	-0.022	0.004	-0.028
	80	80	80	80	26	26	26	26
2023-03-22	-0.002	-0.021 (∗|)	-0.016 (∗∗|∗∗)	-0.035 (∗∗|∗∗∗)	-0.041 (∗|∗)	-0.005	-0.045 (∗∗|∗∗)	-0.011

	81	81	81	81	23	23	26	26
2023-05-03	-0.005	-0.009	0.005	0.002	-0.004	0.028	-0.002	0.029
	79	79	80	80	23	23	23	23
2023-06-14	-0.024 (**|*)	-0.027	-0.019 (**|**)	-0.021	-0.01	-0.003	-0.013	-0.006
	79	79	80	80	26	26	26	26
2023-07-26	0.003	-0.005	0.01 (|*)	0.002	-0.02	-0.027	-0.01	-0.017
	79	78	80	79	26	26	26	26
2023-09-20	0.012	0.019 (|**)	0.004	0.011	-0.012	-0.022	-0.008	-0.017
	80	80	80	80	26	26	26	26
2023-11-01	0.006	0.012	0.003	0.009	-0.025 (|*)	-0.035 (|**)	-0.02	-0.034 (|*)
	81	81	81	81	26	23	26	23
2023-12-13	0.003	-0.013	0.004	-0.013	-0.015	-0.058 (*|**)	-0.023	-0.065 (**|***)
	83	83	83	83	26	26	26	26
ECB								
2022-04-14	0.004	-	0.003	-	-0.003	0.001	-0.007	-0.003
	84	0	84	0	21	21	21	21
2022-06-09	0	0.003	0.004	0.007	-0.015 (|*)	0.007	-0.011	0.011
	83	82	83	82	23	23	23	23
2022-07-21	-0.009	-0.017 (*|**)	-0.006	-0.02 (|*)	-0.016	-0.034	0.005	-0.013
	80	79	81	80	24	24	24	24
2022-09-08	0.014	0.004	-0.001	-0.011	0.021	0.01	0.003	-0.008
	82	82	82	82	25	25	25	25
2022-10-27	0.016	0.028 (|*)	0.011	0.023 (*|**)	-0.018	0.008	0.005	0.031
	81	80	81	80	26	26	26	26
2022-12-15	0.007	0.015	0.01	0.018	-0.002	0.017	0.001	0.021
	79	79	79	79	26	26	26	26
2023-02-02	-0.005	0.002	-0.003	0.004	-0.027	-0.025	-0.031	-0.029
	80	80	80	80	26	26	26	26
2023-03-16	-0.004	-0.038 (**|*)	0.01	-0.024 (*|)	0.062 (**|**)	0.059 (*|*)	0.016	0.013
	80	80	80	80	26	26	26	26
2023-05-04	0.002	0.01	-0.003	0.005	0.028	0.025	0.023	0.025
	80	80	81	81	23	23	26	26
2023-06-15	-0.021	-0.022	-0.003	-0.003	-0.006	0.006	0.008	0.02
	80	80	80	80	26	26	26	26
2023-07-27	0.002	-0.005	-0.008	-0.015	-0.016	-0.022	-0.007	-0.012
	79	79	79	79	26	26	26	26
2023-09-14	-0.005	0.001	0.003	0.009	0	0.001	-0.007	-0.006
	80	80	80	80	26	26	26	26
2023-10-26	0.02 (|*)	0.004	0.012	-0.002	-0.018	-0.019	-0.004	-0.004
	78	77	80	79	25	25	25	25
2023-12-14	-0.013	-0.028 (*|*)	-0.016	-0.031 (**|**)	-0.065 (**|***)	-0.077 (**|***)	-0.042 (**|**)	-0.054 (**|**)
	83	83	83	83	26	26	26	26

This table presents $\overline{CAR}(t_1, t_2)$ and $\overline{\Delta CAS}(t_1, t_2)$ for U.S. insurers in response to interest rate decisions by the Fed and the ECB, measured across different event windows. Values are rounded to the third decimal place and calculated according to Eq. (13)–Eq. (18). Statistical significance is assessed using the parametric test of Boehmer et al. (1991), adjusted by Kolari and Pynnönen (2010), and the nonparametric test of Corrado and Zivney (1992). The corresponding p values are based on a two-sided significance test: $^{*}p$<0.1; $^{**}p$<0.05; $^{***}p$<0.01. The first value in parentheses indicates the significance of the parametric test; the second refers to the nonparametric test. The number below each result indicates the portfolio size. The MSCI World Index is used as a proxy for the stock market portfolio, while the iTraxx CDX IG 5-years Index serves as a proxy for the CDS market portfolio.

Table 11: Eurozone Banks' Market Reactions to Fed and ECB Announcements

<table>
<tr><th></th><th colspan="4">Stock Market: $\overline{CAR}(t_1, t_2)$</th><th colspan="4">CDS Market: $\overline{\Delta CAS}(t_1, t_2)$</th></tr>
<tr><th>**Fed**</th><th>(-1;0)</th><th>(-1;+1)</th><th>(0;0)</th><th>(0;+1)</th><th>(-1;0)</th><th>(-1;+1)</th><th>(0;0)</th><th>(0;+1)</th></tr>
<tr><td>2022-01-26</td><td>0.034 (**|***)</td><td>0.046 (**|***)</td><td>0.016 (*|**)</td><td>0.028 (**|***)</td><td>0.005</td><td>-0.001</td><td>-0.005</td><td>-0.011</td></tr>
<tr><td></td><td>71</td><td>71</td><td>71</td><td>71</td><td>47</td><td>47</td><td>47</td><td>47</td></tr>
<tr><td>2022-03-16</td><td>0.019</td><td>0</td><td>0.026 (*|**)</td><td>0.007</td><td>0.004</td><td>0.002</td><td>-0.004</td><td>-0.006</td></tr>
<tr><td></td><td>71</td><td>71</td><td>71</td><td>71</td><td>47</td><td>47</td><td>47</td><td>47</td></tr>
<tr><td>2022-05-04</td><td>-0.017</td><td>-0.003</td><td>-0.023 (|*)</td><td>-0.009</td><td>0.007</td><td>0.001</td><td>-0.002</td><td>-0.008</td></tr>
<tr><td></td><td>59</td><td>59</td><td>71</td><td>71</td><td>46</td><td>46</td><td>46</td><td>46</td></tr>
<tr><td>2022-06-15</td><td>0.011</td><td>0.012</td><td>0.005</td><td>0.003</td><td>0.015</td><td>0.016</td><td>0.001</td><td>0.002</td></tr>
<tr><td></td><td>65</td><td>63</td><td>72</td><td>70</td><td>46</td><td>46</td><td>46</td><td>46</td></tr>
<tr><td>2022-07-27</td><td>-0.001</td><td>-0.011</td><td>-0.001</td><td>-0.011</td><td>-0.012</td><td>-0.013</td><td>0.01</td><td>0.009</td></tr>
<tr><td></td><td>72</td><td>72</td><td>72</td><td>72</td><td>47</td><td>47</td><td>47</td><td>47</td></tr>
<tr><td>2022-09-21</td><td>-0.002</td><td>0.009</td><td>0.001</td><td>0.011</td><td>0.032 (*|*)</td><td>0.034 (|*)</td><td>-0.003</td><td>0</td></tr>
<tr><td></td><td>70</td><td>70</td><td>71</td><td>71</td><td>47</td><td>47</td><td>47</td><td>47</td></tr>
<tr><td>2022-11-02</td><td>0.02 (*|*)</td><td>0.027 (*|**)</td><td>0.011</td><td>0.018 (|*)</td><td>-0.013</td><td>-0.006</td><td>0.007</td><td>0.013</td></tr>
<tr><td></td><td>66</td><td>66</td><td>66</td><td>66</td><td>47</td><td>47</td><td>47</td><td>47</td></tr>
<tr><td>2022-12-14</td><td>0.01</td><td>0.008</td><td>0.004</td><td>0.001</td><td>0</td><td>0.002</td><td>0.005</td><td>0.007</td></tr>
<tr><td></td><td>69</td><td>69</td><td>69</td><td>69</td><td>47</td><td>47</td><td>47</td><td>47</td></tr>
<tr><td>2023-02-01</td><td>0.001</td><td>-0.008</td><td>0.002</td><td>-0.007</td><td>-0.006</td><td>-0.016</td><td>0.002</td><td>-0.007</td></tr>
<tr><td></td><td>69</td><td>69</td><td>69</td><td>69</td><td>47</td><td>47</td><td>47</td><td>47</td></tr>
<tr><td>2023-03-22</td><td>0.015</td><td>0.001</td><td>-0.008</td><td>-0.022 (*|**)</td><td>-0.056 (**|**)</td><td>-0.045</td><td>-0.016</td><td>-0.005</td></tr>
<tr><td></td><td>69</td><td>69</td><td>69</td><td>69</td><td>47</td><td>47</td><td>47</td><td>47</td></tr>
<tr><td>2023-05-03</td><td>-</td><td>-</td><td>0</td><td>-0.009</td><td>0.004</td><td>0.001</td><td>0.014</td><td>0.012</td></tr>
<tr><td></td><td>0</td><td>0</td><td>68</td><td>68</td><td>47</td><td>47</td><td>47</td><td>47</td></tr>
<tr><td>2023-06-14</td><td>0.002</td><td>-0.004</td><td>0.005</td><td>-0.001</td><td>0.013</td><td>0.025 (|**)</td><td>-0.005</td><td>0.008</td></tr>
<tr><td></td><td>69</td><td>69</td><td>69</td><td>69</td><td>47</td><td>47</td><td>47</td><td>47</td></tr>
<tr><td>2023-07-26</td><td>0.001</td><td>0.004</td><td>0</td><td>0.003</td><td>0.005</td><td>-0.008</td><td>0.006</td><td>-0.007</td></tr>
<tr><td></td><td>71</td><td>71</td><td>71</td><td>71</td><td>47</td><td>47</td><td>47</td><td>47</td></tr>
<tr><td>2023-09-20</td><td>0.015 (|*)</td><td>0.026 (|**)</td><td>0.01</td><td>0.021 (|**)</td><td>0.012</td><td>0.016</td><td>0.021</td><td>0.025</td></tr>
<tr><td></td><td>71</td><td>70</td><td>71</td><td>70</td><td>47</td><td>47</td><td>47</td><td>47</td></tr>
<tr><td>2023-11-01</td><td>-0.003</td><td>-0.006</td><td>-0.002</td><td>-0.005</td><td>0.001</td><td>0.002</td><td>0.002</td><td>0.003</td></tr>
<tr><td></td><td>66</td><td>66</td><td>66</td><td>66</td><td>47</td><td>47</td><td>47</td><td>47</td></tr>
<tr><td>2023-12-13</td><td>-0.013 (|**)</td><td>-0.019 (|**)</td><td>-0.008 (*|**)</td><td>-0.015 (|*)</td><td>-0.003</td><td>-0.011</td><td>-0.004</td><td>-0.013</td></tr>
<tr><td></td><td>70</td><td>70</td><td>70</td><td>70</td><td>47</td><td>47</td><td>47</td><td>47</td></tr>
<tr><td>**ECB**</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>2022-04-14</td><td>0.004</td><td>-</td><td>0.01</td><td>-</td><td>-0.01</td><td>-0.016</td><td>0.001</td><td>-0.005</td></tr>
<tr><td></td><td>71</td><td>0</td><td>71</td><td>0</td><td>47</td><td>47</td><td>47</td><td>47</td></tr>
<tr><td>2022-06-09</td><td>0.009</td><td>-0.007</td><td>0.008</td><td>-0.008</td><td>0.002</td><td>0.001</td><td>0.001</td><td>0</td></tr>
<tr><td></td><td>72</td><td>72</td><td>72</td><td>72</td><td>46</td><td>46</td><td>46</td><td>46</td></tr>
<tr><td>2022-07-21</td><td>-0.008</td><td>-0.013</td><td>-0.001</td><td>-0.006</td><td>-0.026</td><td>-0.036</td><td>0.001</td><td>-0.009</td></tr>
<tr><td></td><td>72</td><td>72</td><td>72</td><td>72</td><td>46</td><td>46</td><td>47</td><td>47</td></tr>
<tr><td>2022-09-08</td><td>0.007</td><td>0.016</td><td>0.014</td><td>0.023</td><td>0.007</td><td>0.012</td><td>0.005</td><td>0.009</td></tr>
<tr><td></td><td>71</td><td>71</td><td>71</td><td>71</td><td>47</td><td>47</td><td>47</td><td>47</td></tr>
<tr><td>2022-10-27</td><td>0.007</td><td>-0.001</td><td>0.008</td><td>-0.001</td><td>-0.028 (*|*)</td><td>-0.015</td><td>-0.026 (**|*)</td><td>-0.013</td></tr>
<tr><td></td><td>66</td><td>59</td><td>66</td><td>59</td><td>47</td><td>47</td><td>47</td><td>47</td></tr>
<tr><td>2022-12-15</td><td>0.001</td><td>0.015</td><td>-0.002</td><td>0.011</td><td>0.006</td><td>0.015</td><td>0.002</td><td>0.011</td></tr>
<tr><td></td><td>69</td><td>69</td><td>69</td><td>69</td><td>47</td><td>47</td><td>47</td><td>47</td></tr>
<tr><td>2023-02-02</td><td>-0.007</td><td>-0.002</td><td>-0.009</td><td>-0.004</td><td>-0.006</td><td>-0.009</td><td>-0.009</td><td>-0.011</td></tr>
<tr><td></td><td>69</td><td>69</td><td>69</td><td>69</td><td>47</td><td>47</td><td>47</td><td>47</td></tr>
<tr><td>2023-03-16</td><td>-0.059 (***|***)</td><td>-0.074 (***|***)</td><td>-0.006</td><td>-0.022 (*|*)</td><td>0.08 (**|**)</td><td>0.087 (*|**)</td><td>0.057 (***|***)</td><td>0.064 (**|**)</td></tr>
<tr><td></td><td>69</td><td>69</td><td>69</td><td>69</td><td>47</td><td>47</td><td>47</td><td>47</td></tr>
<tr><td>2023-05-04</td><td>-0.009</td><td>0.001</td><td>-0.009</td><td>0</td><td>0.011</td><td>0.02</td><td>-0.003</td><td>0.006</td></tr>
</table>

	68	68	69	69	47	47	47	47
2023-06-15	-0.001	0.003	-0.006	-0.001	0.007	-0.004	0.012 (*|*)	0.001
	69	69	69	69	47	47	47	47
2023-07-27	0.003	0	0.003	0	-0.006	-0.006	-0.012	-0.012
	71	71	71	71	47	47	47	47
2023-09-14	-0.003	0.001	0	0.004	0.003	-0.003	-0.01	-0.015
	71	71	71	71	47	47	47	47
2023-10-26	0.014	0.016	0.008	0.011	-0.017 (|*)	-0.018	-0.018 (**|**)	-0.019
	67	67	67	67	45	45	45	45
2023-12-14	-0.015 (|*)	-0.017	-0.007	-0.009	-0.008	-0.012	-0.006	-0.01
	70	70	70	70	47	47	47	47

This table presents $\overline{CAR}(t_1, t_2)$ and $\overline{\Delta CAS}(t_1, t_2)$ for Eurozone banks in response to interest rate decisions by the Fed and the ECB, measured across different event windows. Values are rounded to the third decimal place and calculated according to Eq. (13)–Eq. (18). Statistical significance is assessed using the parametric test of Boehmer et al. (1991), adjusted by Kolari and Pynnönen (2010), and the nonparametric test of Corrado and Zivney (1992). The corresponding p values are based on a two-sided significance test: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. The first value in parentheses indicates the significance of the parametric test; the second refers to the nonparametric test. The number below each result indicates the portfolio size. The MSCI World Index is used as a proxy for the stock market portfolio, while the iTraxx CDX IG 5-years Index serves as a proxy for the CDS market portfolio.

Table 12: Eurozone Insurers' Market Reactions to Fed and ECB Announcements

	Stock Market: $\overline{CAR}(t_1, t_2)$				CDS Market: $\overline{\Delta CAS}(t_1, t_2)$			
Fed	(-1;0)	(-1;+1)	(0;0)	(0;+1)	(-1;0)	(-1;+1)	(0;0)	(0;+1)
2022-01-26	0.033 (***|***)	0.048 (***|***)	0.016 (*|**)	0.031 (***|***)	0.001	-0.005	-0.004	-0.01 (|*)
	27	27	27	27	11	11	11	11
2022-03-16	0.003	-0.015	0.014	-0.004	0.006	0.002	-0.004	-0.011
	26	26	26	26	11	9	11	9
2022-05-04	-0.009	-0.011	-0.017 (*|*)	-0.018	0.011	-0.019	0.002	-0.028 (**|*)
	24	24	27	27	9	9	9	9
2022-06-15	0.02 (|*)	0.013	0.016 (|*)	0.009	0.008	0.008	-0.013	-0.012
	27	27	27	27	10	10	10	10
2022-07-27	-0.001	-0.012	-0.004	-0.016	0.018	0.021	0.019	0.023
	28	28	28	28	11	11	11	11
2022-09-21	0	0.001	0.008	0.009	0.045 (*|)	0.056	-0.001	0.009
	28	28	28	28	10	10	11	11
2022-11-02	0.009	0.02 (|**)	0.001	0.012	-0.006	0.023	0.017	0.047
	25	25	25	25	11	11	11	11
2022-12-14	-0.002	-0.002	0	-0.001	0.004	-0.021	0.016	-0.008
	28	28	28	28	11	11	11	11
2023-02-01	-0.006	-0.008	-0.003	-0.005	0.013	0.04	0.009	0.036
	27	27	27	27	11	11	11	11
2023-03-22	0.013 (**|)	0.007	-0.005	-0.012 (|**)	-0.06	-0.045	-0.022	-0.011
	26	26	26	26	9	9	11	11
2023-05-03	-	-	0.006	-0.003	-0.017	-0.022	0.017 (**|**)	0.013
	0	0	24	24	9	9	9	9
2023-06-14	-0.001	-0.011	0.002	-0.009	0.009	0.043 (**|*)	-0.015	0.018
	27	27	27	27	9	9	9	9
2023-07-26	0.004	0.008	0.001	0.006	0.009	0.001	0.021	0.013 (*|)
	28	28	28	28	9	9	9	9
2023-09-20	0.005	0.013	0.003	0.011	0.025	0.03	0.033	0.038
	28	28	28	28	9	9	9	9
2023-11-01	0	-0.005	-0.001	-0.006	-0.034	-0.03	-0.02	-0.015

	26	26	26	26	9	9	9	9
2023-12-13	-0.003	-0.017 (∗∗|∗)	-0.003	-0.016 (∗∗|∗)	0.02	0.013	0	-0.007
	28	28	28	28	9	9	9	9
ECB								
2022-04-14	0.007	-	0.012 (∗|∗∗)	-	-0.013	-0.021 (|∗∗)	-0.002	-0.009
	27	0	27	0	9	9	9	9
2022-06-09	0.003	-0.009	0.011	-0.001	-0.016	-0.009	-0.013	-0.007
	27	27	27	27	11	11	11	11
2022-07-21	-0.021 (|∗∗)	-0.018	-0.008	-0.005	-0.052	-0.079 (∗|)	0.013	-0.015
	27	27	27	27	10	10	10	10
2022-09-08	-0.004	0	0.005	0.008	-0.005	-0.007	0	-0.002
	28	28	28	28	10	10	10	10
2022-10-27	0.013	0.015	0.013	0.014	0.013	0.016	0.013	0.017
	26	26	26	26	10	10	10	10
2022-12-15	-0.001	-0.001	-0.001	-0.001	-0.008	-0.013	-0.024	-0.032
	28	28	28	28	11	9	11	9
2023-02-02	-0.005	-0.002	-0.002	0.001	0.038	0.04	0.028	0.029
	27	27	27	27	11	9	11	9
2023-03-16	-0.027 (∗∗|)	-0.045 (∗∗∗|∗∗)	0.004	-0.013	0.048	0.011	0.073 (∗∗∗|∗∗)	0.036
	26	26	26	26	9	9	9	9
2023-05-04	-0.003	0	-0.009	-0.005	0.012	0.027 (|∗∗)	-0.005	0.01
	24	24	26	26	9	9	9	9
2023-06-15	-0.009	-0.009	-0.01	-0.011	0.018	0.013	0.033 (|∗)	0.029
	27	27	27	27	9	9	9	9
2023-07-27	0.006	0.006	0.005	0.004	0.013 (∗∗|)	0.021 (∗∗|)	-0.008	-0.001
	28	28	28	28	9	9	9	9
2023-09-14	0.001	0.004	0.001	0.005	0.006	-0.007	-0.005	-0.017 (|∗∗)
	28	28	28	28	9	9	9	9
2023-10-26	0.008	0.007	0.002	0.002	-0.017	0.002	-0.01	0.009
	26	26	26	26	8	8	8	8
2023-12-14	-0.016 (∗∗|∗)	-0.019 (∗|∗)	-0.014 (∗|∗)	-0.016 (∗|)	-0.002	0.001	-0.004	-0.002
	28	28	28	28	9	9	9	9

This table presents $\overline{CAR}(t_1, t_2)$ and $\overline{\Delta CAS}(t_1, t_2)$ for Eurozone insurers in response to interest rate decisions by the Fed and the ECB, measured across different event windows. Values are rounded to the third decimal place and calculated according to Eq. (13)–Eq. (18). Statistical significance is assessed using the parametric test of Boehmer et al. (1991), adjusted by Kolari and Pynnönen (2010), and the nonparametric test of Corrado and Zivney (1992). The corresponding p values are based on a two-sided significance test: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. The first value in parentheses indicates the significance of the parametric test; the second refers to the nonparametric test. The number below each result indicates the portfolio size. The MSCI World Index is used as a proxy for the stock market portfolio, while the iTraxx CDX IG 5-years Index serves as a proxy for the CDS market portfolio.

3.5.2 Regression

3.5.2.1 Fed

In the next step, we discuss the regression results of the Fed events. The analysis of U.S. bank stocks uncovers a pronounced negative relationship with both the $target^F$ and *path* factors, as all coefficients are negative and statistically significant at the 1% level. This implies that an increase in the Fed funds rate beyond expectations negatively impacts shareholders, which similarly applies to the future path of interest rates, as expressed by the *path* factor. This is consistent with the results of the univariate analysis, in which we concluded—based on the significant $\overline{CAR}$ and the monetary policy factors—that a contractionary monetary policy lowers stock prices. Conversely, these factors affect U.S. banks' creditors in the opposite direction. We observe a predominantly positive, risk-increasing effect for the $target^F$ factor, which also applies to the *path* factor. These findings are likewise consistent with the univariate analysis. Theoretical considerations regarding stock and CDS market reactions have already been addressed in the context of the univariate analysis.

A similar, albeit weaker, pattern can be observed among U.S. insurers. Here, too, contractionary shocks negatively affect stocks. The $target^F$ coefficients are significant and negative at least at the 10% level in three out of four estimations, while the coefficients of the *path* factors are significant and negative at the 5% level in two estimations. Again, these results are consistent with the findings from the univariate analysis. The dummy variable LIFE exhibits a significantly negative effect in the regression for the (0;+1) event window. Life insurers could be affected, as they enter into long-term obligations and rely heavily on stable interest income. Regarding the CDS market, the $target^F$ factor does not impact creditors of U.S. insurers. The $target^F$ factor captures unexpected short-term interest rate changes, affecting short-term refinancing conditions. Insurers, however, predominantly rely on long-term funding and are therefore less sensitive to short-term interest rate fluctuations than banks. While the $target^F$ factor has a weaker impact on insurers' stock prices compared to banks, it still exhibits a significant effect. However, the fact that this factor appears irrelevant from a creditor's perspective may be related to the predominance of long-term funding as a key risk factor—one that is largely independent of the $target^F$ factor. All coefficients of the *path* factor are positive and significant at least at the 10% level, indicating that the prospect of persistently higher interest rates raises risk. Given insurers' reliance on long-term funding, such expectations imply deteriorating refinancing conditions and, consequently, higher perceived risk. Distinguishing between life insurers and other insurers is irrelevant from the perspective of creditors.

The influence of the $target^F$ factor on the U.S. stocks is generally consistent with Gürkaynak et al. (2005). The presence of additional significant *path* coefficients is likely due to our focus on the stocks of interest rate-sensitive banks and insurers rather than the returns of the broader S&P 500 index. However, the R^2 in our regressions is considerably lower. While Gürkaynak et al. (2005) use high-frequency returns of the S&P 500 as their dependent variable, our analysis relies on firm-level CARs, measured over periods of up to three days. First, individual stock returns display greater idiosyncratic variation compared to index returns; second, the use of longer event windows increases noise, which may account for the lower explanatory power observed in our results.

We have already discussed the spillover effects of the Fed on Eurozone capital markets in the previous section. In the case of stocks, we observed that market reactions were contrary to those in the U.S. This pattern is confirmed by the regression results. For insurers, we observe three significantly positive $target^F$ coefficients at the 1% level, which also holds for *path* coefficients in two out of four regressions. The distinction between life insurers and other insurers remains insignificant. While the coefficients of the *path* factor for banks are significant at the 1% level in all four estimations, the $target^F$ coefficients are also significant at the 1% level in two estimations—

however, once positively in the (-1;0) window and once negatively in the (0;+1) window. In summary, contractionary Fed shocks have a positive effect on the stocks of Eurozone banks and insurers. This inverse effect compared to U.S. stocks is attributed to the fact that positive and negative Fed monetary shocks reduce or raise U.S. stock returns via the discount factor. This, in turn, makes Eurozone bank and insurer stocks more attractive ceteris paribus, ultimately triggering capital flows.

We demonstrate the spillover effects analogously for Eurozone creditors. In the first analysis step, we suggested that contractionary shocks increase CDS spreads and vice versa. For banks, a negative and significant coefficient at the 5% level is observed for the $target^F$ factor in the estimations for the (-1;0) window. The coefficients of the *path* factor are positive and significant in three out of four estimations, which is consistent with the previous argumentation. However, for insurers, we observe significantly negative coefficients for the $target^F$ factor, while the *path* factor remains insignificant. The dummy variable LIFE is significantly negative in two out of four cases at the 5% and 10% levels. This contradicts previous results. However, it is important to emphasize that our regression analysis accounts for all events, whereas in the previous section, we focused solely on significant $\overline{CAR}$ and $\overline{\Delta CAS}$ and attempted to explain them using monetary shocks. Given that significant $\overline{\Delta CAS}$ can only be observed in six out of 16 events, with three of these events showing significance at only the 10% level for one test, it seems plausible that the previously discussed relationship may not be particularly strong.

3.5.2.2 ECB

In a further step, we turn our attention to the ECB events. The stock and CDS market reactions are measured over event windows of up to three days, while the monetary policy factors are derived from interest rate changes within minutes around the press release and press conference. This temporal incongruence implies that the effects of the press release and press conference windows on the capital market cannot be measured separately—in contrast to Altavilla et al. (2019).

For U.S. bank stocks, we observe a mixed picture with both positive and negative significant $target^E$ coefficients. In three out of four estimations, the *timing* factor is positive and at least significant at the 5% level. The *FG* factor is negative and significant at the 1% level across all four estimations. Similar to the $target^E$ factor, the coefficients of the *QE* factor present a mixed pattern, with both significantly positive and negative values. This is in line with the ambiguity of the responses observed in the univariate analysis. In contrast, three out of four $target^E$ coefficients are significantly negative in the estimations for U.S. insurance stocks. Similar to U.S. banks, insurers also exhibit positive and significant coefficients for the *timing* factor. Furthermore, we observe that life insurers, compared to other insurers, negatively impact CARs, as two dummy coefficients are negative and significant at the 5% and 1% levels, which is explained by the long-term interest rate sensitivity of their business. Regarding the U.S. banks' CDS, the $target^E$, *FG*, and *QE* factors have a consistently positive, i.e., risk-increasing effect. Analogous, we observe exclusively positive coefficients for insurance creditors. Specifically, we find two significant *target*^{E} coefficients, two significant *timing* coefficients, three significant *FG* coefficients, and two significant *QE* coefficients. In contrast to the stock reaction of insurers, life insurers do not experience diverging CDS spreads. These findings are consistent with the univariate analysis, in which we concluded that contractionary monetary policy increases U.S. CDS spreads, and vice versa.

Regarding the Eurozone stock market, we observe a similar pattern for banks and insurers. The *target*^{E} coefficients are negative and significant at the 1% level in three estimations for banks and in two estimations for insurers. In this context, the ECB's monetary policy represents a textbook example of a monetary shock impacting Eurozone stocks. In contrast, the *timing* factor has a positive and significant influence on CARs, similarly to the regressions of U.S. stocks. An explanation for the positive influence of the *timing* factor on bank stocks lies in the asymmetric adjustment of interest rates on loans and deposits. Empirical studies indicate that banks promptly incorporate rising market rates into loan pricing, while deposit rates initially tend to remain unchanged, thereby widening the net interest margin (e.g. Albertazzi and Gambacorta, 2009; Deutsche Bundesbank, 2023). The *timing* factor peaks at a six-month maturity, suggesting that banks are able to realize elevated net interest margins within this period due to higher rates. Nevertheless, this effect does not persist, as evidenced by the significantly negative *FG* coefficients. This is consistent with Altavilla et al. (2019). While the *QE* factor has a negligible impact on bank stocks, we observe a positive and at the 1% level significant effect on insurers' CARs in three estimations. The *QE* factor is constructed to have a unit effect on the 10-year OIS rate, meaning that positive values indicate rising long-term interest rates, which correspond to a reduction in QE and thus a contractionary policy. This positive effect on insurance shareholders is linked to their interest rate-sensitive long-term business. The dummy variable LIFE has no impact on insurers. The performance of the Eurozone stock market aligns with the findings of the univariate analysis, which indicated that contractionary monetary policy negatively affects stocks.

With respect to the CDSs, we observe that for banks, the *target*^{E} and *FG* coefficients are significantly positive at the 1% level across all estimations. This effect is the mirror image of the impact on stocks. An increase in interest rates raises the default risk for banks and insurers. This effect is further reinforced when the ECB signals through FG that interest rates will remain elevated in the long term, indicating prolonged financial constraints. Additionally, the *QE* coefficients are significantly positive in all estimations. For insurers, only the risk-increasing effect of the *target*^{E} factor can be observed.

Examining the explanatory power of the stock market regressions, we see that the R^2 values for Eurozone banks and insurers are significantly higher than for their U.S. counterparts. For U.S. banks, the R^2 values range from 3.8% to a maximum of 6.1%, whereas for Eurozone banks, with the exception of the (0;0) window value of 2.8%, the values range between 11.5% and 29.1%. This is plausible, as ECB policy is likely to be more relevant for Eurozone banks than for U.S. banks. A similar pattern is observed for insurer stocks. However, such differences in explanatory power are not observed in the regressions of CDS market reactions, as the R^2 values remain at a similar level. This can be explained by the fact that CDS samples include exclusively large banks and insurers, which are inherently more internationally connected than small local banks.

Table 13: Cross-Sectional Analysis of U.S. Banks' Market Reactions to Monetary Policy Shocks

	Stock Market: $CAR_i(t_1,t_2)$				CDS Market: $\Delta CAS_i(t_1,t_2)$			
Fed	(-1;0)	(-1;+1)	(0;0)	(0;+1)	(-1;0)	(-1;+1)	(0;0)	(0;+1)
target^F	-0.248^{***}	-0.475^{***}	-0.238^{***}	-0.464^{***}	-0.292	0.372^{**}	-0.336^{*}	0.328^{*}
	(0.023)	(0.031)	(0.019)	(0.028)	(0.200)	(0.188)	(0.172)	(0.181)
path	-0.040^{***}	-0.060^{***}	-0.034^{***}	-0.054^{***}	0.041	0.085^{**}	0.009	0.053^{*}
	(0.004)	(0.006)	(0.004)	(0.005)	(0.026)	(0.033)	(0.017)	(0.028)
Constant	0.002^{**}	0.002^{*}	0.002^{**}	0.002^{**}	-0.020^{***}	-0.024^{***}	-0.014^{***}	-0.018^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.005)	(0.002)	(0.004)
Obs.	5233	5195	5270	5225	155	155	156	156
R^2	0.020	0.030	0.019	0.040	0.057	0.033	0.063	0.022
ECB								
target^E	0.001^{***}	-0.001^{***}	0.001^{***}	-0.001^{***}	0.006^{**}	0.007^{*}	0.003	0.004
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.002)	(0.003)	(0.002)	(0.003)
timing	0.001^{**}	0.001	0.003^{***}	0.003^{***}	-0.004	-0.005	-0.003	-0.005
	(0.0004)	(0.001)	(0.0003)	(0.0004)	(0.005)	(0.007)	(0.003)	(0.005)
FG	-0.002^{***}	-0.003^{***}	-0.0003^{***}	-0.001^{***}	0.002	0.004^{**}	0.003^{*}	0.005^{***}
	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.002)	(0.002)	(0.001)	(0.002)
QE	0.0002	0.002^{***}	-0.0004^{***}	0.001^{***}	0.006^{***}	0.007^{***}	0.003^{**}	0.003^{*}
	(0.0001)	(0.0003)	(0.0001)	(0.0003)	(0.001)	(0.002)	(0.001)	(0.002)
Constant	0.005^{***}	0.018^{***}	0.003^{***}	0.012^{***}	-0.0001	-0.003	-0.005	-0.008^{**}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.005)	(0.004)	(0.004)
Obs.	4237	3898	4277	3929	123	122	123	122
R^2	0.040	0.061	0.038	0.042	0.288	0.243	0.191	0.179

This table presents the monetary policy shocks explaining $CAR_i(t_1,t_2)$ and $\Delta CAS_i(t_1,t_2)$ of U.S. banks in response to interest rate decisions by the Fed and the ECB. $CAR_i(t_1,t_2)$ and $\Delta CAS_i(t_1,t_2)$ are computed according to Eq. (13)–Eq. (16).

The MSCI World serves as a proxy for the stock market portfolio, while the iTraxx CDX IG 5-year index is used as a proxy for the CDS market portfolio. Following Eq. (26), monetary shocks for the Fed and the ECB are identified through PCA, as described in Sec. 3.4.4. Regressions are estimated using OLS, with standard errors clustered at the bank level and reported in parentheses. The corresponding p values are based on a two-sided significance test: $^{*}p$<0.1; $^{**}p$<0.05; $^{***}p$<0.01.

Table 14: Cross-Sectional Analysis of U.S. Insurers' Market Reactions to Monetary Policy Shocks

	Stock Market: $CAR_i(t_1,t_2)$				CDS Market: $\Delta CAS_i(t_1,t_2)$			
Fed	(-1;0)	(-1;+1)	(0;0)	(0;+1)	(-1;0)	(-1;+1)	(0;0)	(0;+1)
target^F	−0.036	−0.158*	−0.103*	−0.248***	−0.170	0.123	−0.137	0.164
	(0.064)	(0.088)	(0.062)	(0.070)	(0.108)	(0.163)	(0.094)	(0.159)
path	−0.021**	−0.010	−0.018**	−0.003	0.030*	0.048**	0.037***	0.056***
	(0.009)	(0.013)	(0.008)	(0.010)	(0.016)	(0.023)	(0.011)	(0.021)
LIFE	0.001	−0.005	−0.001	−0.007**	0.009	0.002	0.0002	−0.007
	(0.002)	(0.003)	(0.002)	(0.003)	(0.006)	(0.008)	(0.004)	(0.007)
Constant	−0.0003	−0.004*	−0.002	−0.005***	−0.016***	−0.012***	−0.013***	−0.010***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)
Obs.	1297	1293	1302	1297	397	394	401	398
R^2	0.005	0.004	0.004	0.017	0.028	0.012	0.062	0.024
ECB								
target^E	−0.0003*	−0.002***	0.0001	−0.001***	0.002***	0.001**	0.0004	−0.0003
	(0.0002)	(0.0003)	(0.0001)	(0.0003)	(0.001)	(0.001)	(0.0004)	(0.0005)
timing	0.004***	0.003*	0.001	0.001	0.005**	0.003	0.003**	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)
FG	−0.0001	−0.0003	0.001***	0.001	0.001*	0.002**	0.001	0.002**
	(0.0003)	(0.001)	(0.0002)	(0.0005)	(0.001)	(0.001)	(0.001)	(0.001)
QE	0.001**	0.001	0.0004	0.001	0.002***	0.002**	−0.0003	−0.0004
	(0.0004)	(0.001)	(0.0003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
LIFE	−0.007***	−0.008**	−0.003	−0.003	−0.006	−0.008	−0.007	−0.009
	(0.003)	(0.003)	(0.002)	(0.003)	(0.007)	(0.009)	(0.006)	(0.008)

Constant	0.006***	0.008**	0.003**	0.003	−0.002	0.002	−0.001	0.003
	(0.002)	(0.003)	(0.001)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Obs.	1046	958	1050	962	323	323	326	326
R^2	0.020	0.045	0.014	0.026	0.156	0.095	0.024	0.030

This table presents the monetary policy shocks explaining $CAR_i(t_1, t_2)$ and $\Delta CAS_i(t_1, t_2)$ of U.S. insurers in response to interest rate decisions by the Fed and the ECB. $CAR_i(t_1, t_2)$ and $\Delta CAS_i(t_1, t_2)$ are computed according to Eq. (13)–Eq. (16). The MSCI World serves as a proxy for the stock market portfolio, while the iTraxx CDX IG 5-year index is used as a proxy for the CDS market portfolio. Following Eq. (26), monetary shocks for the Fed and the ECB are identified through PCA, as described in Sec. 3.4.4. Regressions are estimated using OLS, with standard errors clustered at the bank level and reported in parentheses. The corresponding p values are based on a two-sided significance test: $^{*}p$<0.1; $^{**}p$<0.05; $^{***}p$<0.01.

Table 15: Cross-Sectional Analysis of Eurozone Banks' Market Reactions to Monetary Policy Shocks

	Stock Market: $CAR_i(t_1, t_2)$				CDS Market: $\Delta CAS_i(t_1, t_2)$			
Fed	(-1;0)	(-1;+1)	(0;0)	(0;+1)	(-1;0)	(-1;+1)	(0;0)	(0;+1)
target^F	0.189***	0.039	0.024	−0.164***	−0.251**	−0.163	−0.043	0.045
	(0.044)	(0.050)	(0.035)	(0.045)	(0.098)	(0.147)	(0.052)	(0.133)
path	0.025***	0.015**	0.035***	0.022***	0.053***	0.068***	0.008	0.022*
	(0.006)	(0.008)	(0.005)	(0.006)	(0.011)	(0.015)	(0.007)	(0.013)
Constant	0.005***	0.005***	0.0003	−0.0003	−0.002	−0.004	0.001	0.00003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Obs.	1028	1025	1116	1113	750	750	750	750
R^2	0.019	0.003	0.057	0.046	0.085	0.050	0.005	0.004
ECB								
target^E	−0.002***	−0.003***	−0.0001	−0.001***	0.002***	0.002***	0.002***	0.002***
	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0004)	(0.001)	(0.0003)	(0.0004)
timing	0.005***	0.011***	0.002***	0.008***	−0.00004	0.001	−0.002	−0.0004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
FG	−0.001***	−0.0004	−0.0005***	0.0001	0.002***	0.003***	0.002***	0.002***
	(0.0002)	(0.0003)	(0.0001)	(0.0003)	(0.0004)	(0.0005)	(0.0003)	(0.0004)
QE	−0.001*	−0.001	0.0003	0.00002	0.002***	0.003***	0.001*	0.001**
	(0.0003)	(0.001)	(0.0002)	(0.0004)	(0.001)	(0.001)	(0.0004)	(0.0005)

Constant	0.002*	0.003	0.003***	0.003**	−0.002	−0.002	−0.005***	−0.004***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Obs.	905	827	906	828	607	607	608	608
R^2	0.248	0.291	0.028	0.115	0.171	0.157	0.174	0.139

This table presents the monetary policy shocks explaining $CAR_i(t_1,t_2)$ and $\Delta CAS_i(t_1,t_2)$ of Eurozone banks in response to interest rate decisions by the Fed and the ECB. $CAR_i(t_1,t_2)$ and $\Delta CAS_i(t_1,t_2)$ are computed according to Eq. (13)–Eq. (16). The MSCI World serves as a proxy for the stock market portfolio, while the iTraxx CDX IG 5-year index is used as a proxy for the CDS market portfolio. Following Eq. (26), monetary shocks for the Fed and the ECB are identified through PCA, as described in Sec. 3.4.4. Regressions are estimated using OLS, with standard errors clustered at the bank level and reported in parentheses. The corresponding p values are based on a two-sided significance test: $^{*}p$<0.1; $^{**}p$<0.05; $^{***}p$<0.01.

Table 16: Cross-Sectional Analysis of Eurozone Insurers' Market Reactions to Monetary Policy Shocks

	Stock Market: $CAR_i(t_1,t_2)$				CDS Market: $\Delta CAS_i(t_1,t_2)$			
Fed	(-1;0)	(-1;+1)	(0;0)	(0;+1)	(-1;0)	(-1;+1)	(0;0)	(0;+1)
target^F	0.221***	0.151***	0.132***	0.042	−0.495***	−0.536**	−0.228**	−0.272*
	(0.042)	(0.056)	(0.035)	(0.050)	(0.182)	(0.215)	(0.106)	(0.163)
path	0.010	−0.0004	0.034***	0.023***	0.034	0.034	−0.009	−0.011
	(0.006)	(0.009)	(0.005)	(0.008)	(0.025)	(0.033)	(0.016)	(0.027)
LIFE	0.001	0.003	0.0002	0.001	−0.014*	−0.017**	−0.007	−0.010
	(0.002)	(0.003)	(0.001)	(0.002)	(0.007)	(0.008)	(0.005)	(0.007)
Constant	0.003***	0.001	0.00002	−0.002	0.007	0.011*	0.006**	0.011**
	(0.001)	(0.002)	(0.001)	(0.002)	(0.005)	(0.006)	(0.003)	(0.005)
Obs.	403	403	430	430	158	156	161	159
R^2	0.061	0.018	0.106	0.020	0.134	0.101	0.035	0.029
ECB								
target^E	−0.001***	−0.002***	0.0001	−0.0003	0.001*	−0.001	0.003***	0.001**
	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.001)	(0.001)	(0.001)	(0.001)
timing	0.001	0.004***	−0.001	0.002**	−0.001	0.002	−0.005**	−0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.004)	(0.002)	(0.003)
FG	−0.001***	−0.001***	−0.0003	−0.001*	−0.0003	−0.001	−0.0004	−0.001

	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.001)	(0.002)	(0.001)	(0.001)
QE	0.001***	0.001**	0.001***	0.0003	0.002	0.003	−0.001	−0.0003
	(0.0003)	(0.001)	(0.0002)	(0.0004)	(0.002)	(0.002)	(0.001)	(0.001)
LIFE	−0.002	−0.003	−0.0001	−0.001	−0.005	−0.002	−0.006	−0.003
	(0.002)	(0.003)	(0.002)	(0.002)	(0.008)	(0.009)	(0.007)	(0.008)
Constant	0.003**	0.004*	0.003***	0.002	0.005	0.006	0.001	0.002
	(0.001)	(0.002)	(0.001)	(0.002)	(0.006)	(0.008)	(0.006)	(0.006)
Obs.	349	322	351	324	125	121	125	121
R^2	0.144	0.202	0.047	0.035	0.046	0.026	0.134	0.034

This table presents the monetary policy shocks explaining $CAR_i(t_1, t_2)$ and $\Delta CAS_i(t_1, t_2)$ of Eurozone insurers in response to interest rate decisions by the Fed and the ECB. $CAR_i(t_1, t_2)$ and $\Delta CAS_i(t_1, t_2)$ are computed according to Eq. (13)–Eq. (16). The MSCI World serves as a proxy for the stock market portfolio, while the iTraxx CDX IG 5-year index is used as a proxy for the CDS market portfolio. Following Eq. (26), monetary shocks for the Fed and the ECB are identified through PCA, as described in Sec. 3.4.4. Regressions are estimated using OLS, with standard errors clustered at the bank level and reported in parentheses. The corresponding p values are based on a two-sided significance test: $^{*}p$<0.1; $^{**}p$<0.05; $^{***}p$<0.01.

3.6 Robustness and Limitations

As previously explained, we calculate abnormal returns using the market model by Sharpe (1963), employing the MSCI World as a proxy for the market portfolio. To ensure robustness, we repeat the analyses using the MSCI Europe for Eurozone stock portfolios and the MSCI USA for U.S. stock portfolios. The corresponding results, presented in G, remain substantially unchanged. In addition, we repeat the cross-sectional analysis based on these alternative benchmarks. The results likewise remain robust and are available from the authors upon request.

A key limitation in analyzing the CDS market is the significantly lower data availability, which is particularly evident for U.S. banks, where the portfolio includes no more than ten CDSs. While U.S. stock portfolios also contain smaller regional banks, the CDSs of U.S. banks primarily represent large banks. This also applies, albeit to a lesser extent, to the other CDS portfolios. Consequently, the findings for the CDS markets are primarily limited to larger financial intermediaries.

Another limitation is that the Fed and the ECB are not the only central banks to have raised interest rates in response to surging inflation. The global inflationary pressures, primarily driven by the COVID-19 pandemic and Russia's war of aggression against Ukraine, have led many central banks worldwide to tighten their monetary policy. One significant challenge arises from the timing of interest rate decisions across different central banks. For instance, the Bank of England, the Swiss National Bank and the Bank of Japan have frequently adjusted their interest rates shortly after the Fed's decisions, often within a day. This creates potential confounding effects, as market reactions may not be solely attributable to the Fed or ECB but could also reflect expectations and spillovers from other major central banks. Moreover, given the interconnectedness of global financial markets, monetary policy decisions in one jurisdiction can influence expectations and asset prices across multiple regions. Investors and financial institutions often anticipate synchronized policy moves among major central banks, which can blur the distinction between the effects of individual policy actions. As a result, some observed market reactions may not be exclusively driven by Fed or ECB announcements but could also incorporate responses to policy decisions from other central banks.

3.7 Conclusion

Primarily due to the COVID-19 pandemic and the Russian war of aggression against Ukraine, inflation in the U.S. and Eurozone has risen significantly. Consequently, since 2022, the Fed and the ECB have departed from the long phase of low interest rates and have successively raised rates. In this study, we build on these developments and examine, using an event study, the effects on shareholders and creditors of U.S. and Eurozone banks and insurers. This investigation of banks and insurers is particularly interesting because, as financial intermediaries operating with an interest rate-sensitive business model, there exist various theoretical considerations as to why profitability and risk change. We extend the existing literature by including CDSs, which enables us to investigate the impact on risk from the perspective of creditors, while stocks primarily reflect profitability. Moreover, we explore the spillover effects of Fed policy into Eurozone capital markets and vice versa. As Altavilla et al. (2019) note, the transmission of ECB policy in non-euro countries has been little investigated and thus represents a further important contribution to the literature. Since markets theoretically react only when the policies of the Fed and the ECB have not been priced in, we compute monetary shocks using the methodologies of Gürkaynak et al. (2005) and Altavilla et al. (2019). These serve to explain the abnormal stock and CDS market reactions, whereby the firm-level CARs and ΔCAS are subsequently regressed on the monetary policy shocks.

In response to Fed events, we observe a clear pattern among U.S. stocks: contractionary shocks lead to negative reactions, with both the $target^F$ and *path* factors exhibiting negative effects. A higher discount rate depresses stock prices and boosts fixed-income appeal, aligning with textbook monetary shocks. The effects on the U.S. CDS market suggest that contractionary shocks increase creditor risk, and vice versa. Trading losses, declining credit quality, and reduced credit supply serve as the theoretical explanations for the sensitivity of bank CDSs to interest rate hikes. With regard to insurers, impairment effects on their securities portfolios—comprising predominantly fixed-income instruments—are the prevailing factor. While both the $target^F$ and *path* factors increase risk for bank CDSs, only the *path* factor contributes to elevated risk for insurers. This likely reflects that short-term interest rates are less relevant to credit risk than long-term rates.

We provide evidence for significant spillover effects in Eurozone stocks. Contrary to U.S. stocks, Eurozone shareholders respond positively to contractionary shocks. We document highly significant and positive *path* coefficients, while the $target^F$ coefficients are primarily significant and positive for insurers. The inverse effect arises because Fed shocks alter U.S. shareholder returns via the discount factor, making Eurozone stocks relatively more attractive and triggering capital flows. Moreover, we also observe significant reactions in the Eurozone CDS market. Banks exhibit a similar pattern to their U.S. counterparts, with rising CDS spreads following contractionary shocks—driven in particular by the *path* factor. This similar reaction of U.S. and Eurozone banks can be attributed to the fact that the CDS portfolios comprise only large, cross-border banks. While insurers exhibit significant reactions, the overall pattern remains somewhat ambiguous. However, life insurers exhibit narrower CDS spreads compared to other types of insurers, implying a lower credit risk.

We also find evidence of significant spillover effects in U.S. stock markets in response to ECB events; however, the pattern of market reactions remains ambiguous. One explanation is the market-oriented U.S. financial system with many small publicly listed financial intermediaries that operate only at the local level. This is reflected in the regression analysis of banks, which displays inconclusive positive and negative $target^E$ and *QE* coefficients, while at least the *FG* coefficients are consistently negative and significant. The results for insurers show significantly negative $target^E$ coefficients and indicate a negative impact for life insurers as well. For both banks and insurers, the *timing* factor exhibits a significantly positive effect. With regard to banks, this can be attributed to a temporary increase in the net interest margin, as lending rates are adjusted instantaneously, while deposit rates remain constant for the time being. U.S. creditors react to contractionary policies with increased CDS spreads. In particular, the regressions reveal that the coefficients for the $target^E$, *FG*, and *QE* factors have a risk-increasing effect on bank and insurer CDSs, i.e., they are positive. The U.S. CDS portfolios include only large banks and major insurers, which by their nature operate beyond the domestic market in international financial markets and also maintain branches in the Eurozone.

Eurozone shareholders respond to contractionary ECB shocks with negative abnormal returns and positive abnormal CDS spread changes. This reaction mirrors the response of U.S. markets to Fed policy. From the shareholders' perspective, a contractionary policy reduces return expectations, which aligns with a textbook monetary shock. These findings are reflected in the regressions, where the $target^E$ and *FG* factors negatively influence CARs. Analogously to the U.S. stock regressions, we find significant positive coefficients for the *timing* factor which can be attributed to the same underlying rationale. QE also positively impacts insurer stocks. The increase in long-term interest rates thus positively affects returns, which can be explained by the interest-sensitive and long-term business model of insurers. Creditors perceive a significant increase in risk. The reasons for banks can again be traced to trading losses, a deterioration in credit quality, and a contraction in credit supply, while insurers face valuation losses due to declining market values of interest-sensitive assets. The $target^E$, *FG* and *QE* factors have a positive, i.e., risk-increasing effect on bank ΔCAS, while only the first-mentioned factor increases insurers' risk.

Our results clearly demonstrate that interest rate changes by the Fed and the ECB alter both expected profitability and risk. Additionally, we demonstrate significant spillover effects of U.S. interest rate policy on Eurozone markets and vice versa. While we examine the effects of monetary policy on banks and insurers, incorporate the creditor perspective into the analysis, and investigate the transmission of ECB policy in the U.S., the analysis could be conducted with even greater precision in the future. To more precisely determine the impact of interest rate policy on asset prices, the event study could be conducted at a high-frequency level, given the necessary data is available. If firm-level stock prices and CDS spreads were available on a tick basis, this would reduce the risk of confounding events. Furthermore, it would allow for a separate analysis of the effects of ECB policy during the press release and press conference windows.

3.8 Declaration of Co-authors and Record of Accomplishments

Title:	Surprise, Surprise? Banks' and Insurers' Market Reactions to Interest Rate Hikes
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Conferences:	Presented at "Forschungskolloquium Finanzmärkte"
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Share of Contributions:

Contributions	Jonas Krettek	Anne-Marie Ossig
Research design	90%	10%
Development of research question	90%	10%
Method development and specification	90%	10%
Research performance & analysis	70%	30%
Literature review and framework development	10%	90%
Data collection, preparation and analysis	90%	10%
Analysis and discussion of results	90%	10%
Derivation of implications and conclusions	90%	10%
Manuscript preparation	65%	35%
Final draft	70%	30%
Finalization	60%	40%
Overall contribution	75%	25%

Date, Jonas Krettek

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4 Bitcoin: Like a Satellite or Always Hardcore? A Core–Satellite Identification in the Cryptocurrency Market

4.1 Abstract

CCs have become increasingly interesting for institutional investors' strategic asset allocation and will therefore be a fixed component of professional portfolios in the future. However, this asset class differs from established assets primarily in that it has a higher standard deviation and tail risk. The question then arises whether CCs with similar statistical key figures exist. On this basis, a core market incorporating CCs with comparable properties enables the implementation of a tracking error approach. A prerequisite for this is the segmentation of the CC market into a core and a satellite, with the latter comprising the accumulation of the residual CCs remaining in the complement. Using a concrete example, we segment the CC market into these components based on modern methods from image / pattern recognition.

4.2 Introduction

CCs have gained tremendous attention and popularity in media and society in recent years, not least because of their high market volatility. Due to their nature, CCs are seen more as an investment object than as a currency in the classical sense (Baur et al., 2018). The development of rising investment volumes has been a trend for years, and it can be assumed that CCs are gradually on their way to becoming an established asset class. Against this background, it seems plausible that CCs will become a fixed component of institutional investors' portfolios in the future.

In professional portfolio management, one approach is to segment the investment universe into a core of assets with homogeneous statistical properties and assets that differ significantly from these properties—the so-called satellite. The core market can then be tracked using adequate asset picks with a tracking error approach. The satellite investments represent only a small proportion of the total portfolio and are mostly composed of actively managed sub-portfolios covering selected areas that are meant to deliver above-average returns and have a diversifying effect due to their low correlation with the core investment (Amenc et al., 2012).

In standard portfolios, for example, satellite investments such as geographical regions, asset classes different from the core investment and the purchase of portfolios with different management styles or strategies are suitable for enriching or diversifying the core portfolio. It is also possible to consider a certain asset class and differentiate between core investments and satellite investments. Examples include the sector selection of corporate bonds or the segmentation of stocks into "with the market" (core) and "high beta stocks" (satellite).

In this paper, we investigate specifically the CC asset class and propose a method to segment the core market from the satellite based on the development of key statistical parameters.

Attempts to depict the CC market holistically for reasons of portfolio and risk management have already been investigated in the literature. A prominent series of studies have addressed the construction of an index for CCs. In this context, the CC market index CRIX proposed by Trimborn and Härdle (2018) represents a well-known example and is intended to serve as a starting point to address these economic questions. A similar top-down approach based on the 30 largest CCs by market capitalization has been used to calculate the CC index CCi30 (Rivin et al., 2017).

However, instead of focusing on market capitalization and trading volume and thus prioritizing larger CCs, we identify the core market by applying a core–satellite approach based on the individual risk–return profile. Our approach has some potential advantages compared to a top-down constructed index. While such indices take only the largest CCs into account and may suffer from survivorship bias, the core–satellite approach identifies the core of the market, i.e., those CCs that behave similarly in statistical terms. Although we currently exclusively consider 27 CCs due to data gaps, regarding shifts in perspective as the market grows, it might become possible to use our method to identify the core market from a large number of CCs. To build a portfolio, investors would then no longer need to replicate the indices but could deliberately buy fewer individual assets of the core of the CC universe and combine them with those of the satellite. Since the core market could be represented with fewer assets in the portfolio, the monitoring costs for the portfolio would decrease. Moreover, potential problems in the portfolio, such as price collapses, operational risk (Trimborn et al., 2020) or the extinction of entire CCs, could be countered more quickly. This is a decisive advantage, especially due to the dynamics and speed of the market.

To identify CCs showing a comparable performance from 2014 to 2019, we consider returns as well as standard deviations proposed by traditional portfolio theory (Markowitz, 1952). One general problem is that CCs are different from traditional asset classes, especially in terms of extreme tails and corresponding tail risk. Against this background, Majoros and Zempléni (2018) and Börner et al. (2025) show that the SDI is well suited to statistically model the returns of CCs overall, especially in the tail area. Thus, we extend our database by including the tail parameter α of the SDI to specifically consider the tail risk. To identify similar patterns in the development of statistical parameters, we use the DTW algorithm. This algorithm was originally developed for speech recognition (Sakoe and Chiba, 1978) but is widely used for clustering and classification in various application fields today (Giorgino, 2009).

The DTW analysis leads to DTW distances that are defined in pairs. The question arises if assets—CCs in the present case—can be grouped together in such a way that they are similar in the sense of short DTW distances according to specified criteria, namely, the aforementioned statistical indicators. This would allow assets to be divided into a core and a satellite. The particular difficulty lies in the fact that sorting individual DTW distances becomes a monotonically increasing function over natural numbers, and the possible value range $[0, \infty]$ is almost continuously covered in many cases. On this basis, it must be examined whether a specific DTW distance can be derived purely from the data, acting in further steps as a boundary to divide the investment universe into a core and a satellite. In the following, we present a general procedure that is based on modern methods of pattern recognition and precisely answer these questions, and we systematically show the separation of core assets within an investment universe. The process is not restricted to a specific asset class and can be used wherever it is important to separate similar from dissimilar assets.

Using the development of statistical parameters, we show that segmenting the CC market into a core and a satellite succeeds when applying our method. Furthermore, we answer the question of whether Bitcoin is indeed part of the hard core of the CC market or just a satellite. As the CC market becomes more professional, that is, as market capitalization, liquidity, and market depth increase, our method might become an indispensable tool for professional asset management.

The remainder of this paper is structured as follows: In Sec. 4.3, we describe the data used for our analysis. In Sec. 4.4, a brief overview of the DTW methodology is given. In the main part of our study, Sec. 4.5, we develop the identification method that separates the CC universe into a core market segment and a complementary segment that is an accumulation of the remaining residual CCs—the satellite. The separation procedure is shown using real data. Section 4.6 presents some robustness checks. Section 4.7 summarizes our most important results and gives an overview of further research topics.

4.3 Data

For the foundation of our analysis, we follow various studies by extracting the daily prices of CCs from the website coinmarketcap.com (Fry and Cheah, 2016; Hayes, 2017; Brauneis and Mestel, 2018; Caporale et al., 2018; Gandal et al., 2018; Glas, 2019). To depict the CC market as a whole, we aim to include as many CCs in our analysis as possible. However, there is a trade-off between having the longest time series possible and the number of CCs in the sample because, on average, seven CCs die out per week (ElBahrawy et al., 2017). Against this background, we end up with an observation period from January 1, 2014, to June 1, 2019, taking 66 potential CCs from the CoinMarketCap Market Cap Ranking at the reference date of January 1, 2014, into consideration, as these CCs have been present throughout the entire timeframe.

As data gaps appear in the time series of most CCs, we exclude all CCs with five or more consecutive missing observations. By utilizing the last observation carried forward (LOCF) approach, as previously done in Schmitz and Hoffmann (2020), Trimborn et al. (2020), Börner et al. (2025), we are able to include all CCs with smaller data gaps. Hence, $N = 27$ CCs remain in our dataset, as depicted in Tab. 17. In a next step, we convert the CC closing prices denoted in USD to EUR prices using the daily USD/EUR exchange rates retrieved from Thomson Reuters Eikon. To prevent potential weekday biases, the resulting (daily) observations are converted into weekly observations (Dorfleitner and Lung, 2018; Aslanidis et al., 2020). Intraday data are not considered to further avoid biases, e.g., through pump and dump schemes.

As a starting point, we compute logarithmized weekly returns, which are referred to as returns for the sake of simplicity in the following. On this basis, we calculate the average weekly returns

Table 17: Considered CCs

CC	ID	CC	ID	CC	ID
Anoncoin	ANC	BitBar	BTB	Bitcoin	BTC
CasinoCoin	CSC	Deutsche eMark	DEM	Diamond	DMD
Digitalcoin	DGC	Dogecoin	DOGE	Feathercoin	FTC
FLO	FLO	Freicoin	FRC	GoldCoin	GLC
Infinitecoin	IFC	Litecoin	LTC	Megacoin	MEC
Namecoin	NMC	Novacoin	NVC	Nxt	NXT
Omni	OMNI	Peercoin	PPC	Primecoin	XPM
Quark	QRK	Ripple	XRP	TagCoin	TAG
Terracoin	TRC	WorldCoin	WDC	Zetacoin	ZET

The table presents the 27 considered CCs, with data sourced from CoinMarketCap.

per year as well as the standard deviations and fit the tail parameter α of the SDI. Our longitudinal analysis from 2014 to 2019 allows us to examine the market dynamics of the statistical parameters herein.

4.4 Dynamic Time Warping

As we use three variables simultaneously, a simple correlation analysis is not adequate since it would provide only information about the similarity of a certain statistical variable that has no valid significance for an $N \times N$ matrix with $N = 27$, with a given total of only six annual measuring points. Furthermore, a simple correlation analysis is unable to capture the dynamic character of the development of the statistical parameters. Therefore, we use the DTW algorithm to segment the market into CCs that show similar behavior over the investigated period.

Sigaki et al. (2019) employ this methodology, thereby revealing clusters of CCs with similar informational efficiency. However, they consider only returns as a variable on a smaller time period. Although pursuing a different goal, we also select a DTW distance matrix, but instead of analyzing clusters, we implement pattern recognition to identify core and satellite CCs. Because the DTW algorithm is well known and widely used, only a cursory overview of this method is given in the following, focusing on the features relevant to our analysis.

The DTW distance can be used as a shape-based dissimilarity measure that finds the optimum warping path between two time series by minimizing a cost function (Sakoe and Chiba, 1978; Aghabozorgi et al., 2015). By following the definition and notation of the main literature, in the first step, a so-called distance matrix between each pair of time series compared needs to be calculated. This distance matrix can be based on various metrics. For our analysis and for reasons of robustness, we compute Manhattan, Euclidean and squared Euclidean distance matrices. As explained in Sec. 4.5 in more detail, we use three variables per CC to determine the distance matrices between each pair of (multivariate) time series over the course of 2014 to 2019. We end up with a distance matrix for each of the three metrics and each pair of time series. Note that the distance matrix described thus far is made up of a scheme of six rows and six columns due to the six discrete points in time. For a specific currency pair, each cell in the scheme contains the distance in the respective metric for a specific point in time. In the literature, the latter is also referred to as the *local cost matrix*. The above scheme must be carefully distinguished from the distance matrix $\mathbf{D}$ defined in Sec. 4.5.

Given the distance matrix, i.e., the 6×6 scheme of each CC pair, the DTW algorithm finds the optimal alignment through it starting in each distance matrix at $(2014, 2014)$ and finishing at $(2019, 2019)$ (Sakoe and Chiba, 1978). This implies that the time differences between the time series are eliminated by warping the time axis of one series so that the maximum coincidence is attained with the other (Sakoe and Chiba, 1978). The individual distances of the DTW path are aggregated to total costs using a cost function. The total costs, referred to as the DTW distance d, reflect the minimum costs between the time series compared. For clarity, it should be noted that the DTW distance between the same objects equals 0 since there is no dissimilarity. The upper-left part of Fig. 4 shows the DTW distance d_{uv} for each pair $u, v = 1, \ldots, N$ of the $N = 27$ CCs.

We outline the underlying methodology only briefly, but there are several restrictions and setting options for the algorithm and the cost function. For a more detailed overview, see, e.g., Sakoe and Chiba (1978) and Giorgino (2009).

4.5 Core–Satellite Identification

In strategic asset allocation, a core–satellite strategy is the division of an investment into a portfolio consisting of a broadly diversified core investment that is intended to offer a basic return with moderate risk and several individual investments (satellites) with higher risk and higher earnings potential. The latter serves to increase the return of the overall investment (Methling and von Nitzsch, 2019).

The returns, sample average $\langle r_{cc} \rangle$, standard deviation s_{cc} and tail parameter α are examined as the essential statistical parameters for CCs. A brief overview of the implemented parameterization and the SDI's main features are given in H. The tail parameter α plays a significant role in differentiating between CCs in which the returns almost obey a normal distribution (i.e., $\alpha \to 2$) or possess a long tail (i.e., $\alpha \ll 2$) with correspondingly high tail risks.

Overall, we consider the dynamics of the sample vector $(\langle r_{cc} \rangle, s_{cc}, \alpha)'$ over time from 2014 to 2019 in our analysis. Table 18 shows an exemplary excerpt of four CCs from the whole dataset. The aim is to use the temporal development of the statistical parameters to infer CCs that can be assigned to a market core due to their similar statistical behavior. The three-dimensional vector $(\langle r_{cc} \rangle, s_{cc}, \alpha)'$ is examined over the course of six years, and the DTW distance d_{uv} is determined in pairs, with $u, v = 1, \ldots, N$. The DTW distance is calculated in three different metrics: Manhattan, Euclidean and squared Euclidean. This allows three matrices $\mathbf{D}_{\text{Metric}} \in \mathbb{R}^{N \times N}$ for the CCs to be determined, each for a specific metric, with elements $d_{uv;\text{Metric}}$. These square matrices are symmetrical $d_{vu} = d_{uv}$,

Table 18: Input Data for the DTW Distance Analyses

CC		Value	Sample Vector						DTW Dist.
No.	ID		2014	2015	2016	2017	2018	2019	Metric / d_{uv}
6	DMD	$\langle r_{cc} \rangle$	-4.52	1.67	-0.73	8.46	-5.50	0.85	Manh.
		s_{cc}	28.12	22.96	9.65	20.00	14.37	16.48	6.01
		α	1.81	1.18	2.00	2.00	1.30	2.00	Eucl.
11	FRC	$\langle r_{cc} \rangle$	-7.10	-1.62	-0.25	5.92	-1.97	5.05	3.10
		s_{cc}	18.74	20.27	59.19	44.84	29.43	104.04	sq. Eucl.
		α	2.00	1.44	0.63	1.18	1.51	0.90	5.03
21	XPM	$\langle r_{cc} \rangle$	-7.27	-0.38	-0.58	5.38	-2.98	0.70	Manh.
		s_{cc}	15.58	24.28	8.66	26.47	22.84	13.35	1.06
		α	1.67	1.65	1.79	1.63	1.76	1.57	Eucl.
27	ZET	$\langle r_{cc} \rangle$	-5.74	0.16	0.51	2.88	-3.73	1.11	0.53
		s_{cc}	28.72	24.63	16.39	35.35	20.14	24.01	sq. Eucl.
		α	1.65	1.68	1.72	1.74	1.83	1.80	0.13

This table shows an exemplary excerpt of the statistical characteristics of two selected CC pairs (2014–2019) and the corresponding DTW distances based on three different metrics; return $\langle r_{cc} \rangle$ and standard deviation s_{cc} are in percent per week.

the entries on the diagonal are zero $d_{uu} = 0$, and the off-diagonal elements are all positive.

For the two pairs of CCs in the last column of Tab. 18, the calculated DTW distances in each metric can be compared. Note that the number in the first column corresponds to the numbering in Tab. 19.

The first pair (Diamond (DMD) and Freicoin (FRC)) admirably exhibits a considerable distance in each metric. A detailed analysis of the vectors over time shows the reason for this great distance. On the one hand, clear differences can be observed with regard to the absolute level and the sign (same year) of the returns. On the other hand, there are strong differences in the standard deviation and in the tail parameter (same year). While the standard deviation of the CC Diamond remains almost the same at a high level, the scattering of the returns of the FRC increases dramatically in 2019. For both CCs, it is remarkable that the underlying return distribution changes from almost normal to a heavy-tailed distribution. This can be clearly seen in the year-to-year change in the tail parameter α. Since this change does not occur at the same time (same year) for the two CCs, the DTW analysis results in large distances. Furthermore, we observe this changing distribution behavior with other CCs.

At this point, we recommend that a potentially time-varying and hence nonstationary distribution warrants closer examination to control the risk for institutional investors if CCs represent a significant component of the assets being allocated.

The second pair of CCs (Primecoin (XPM) and Zetacoin (ZET)) illustrates two CCs behaving very similarly. Overall, comparatively small DTW distances can be observed here. The returns, the standard deviations and the tail parameters are closely related. It is also worth noting that the form of the underlying distribution of returns hardly changes; the variability of the tail parameter is likely to derive from statistical errors based on the small database.

The upper-left part of Fig. 4 shows the distance matrix $\mathbf{D}_{\mathrm{SE}}$ for the DTW distances in the squared Euclidean metric as a surface plot for all CCs. The ordering descends from the numbers given in the first column of Tab. 19. The colors indicate the value of the DTW distance from small (white) to large (black), i.e., in this example, from 0 to approximately 5. The entries with zero DTW distance are marked white.

The problem of identifying groupings in the set of CCs leads to the problem of finding structures in the distance matrix $\mathbf{D}_{\mathrm{Metric}}$. One possibility to carry out this structural analysis of the distance matrices is to apply methods that have been used for a long time in the investigation of hierarchical matrices (Liu et al., 2012; Hackbusch, 2015). Similar to image recognition, these methods aim to recognize patterns in matrices.

In the first step, the CCs are rearranged in such a way that the CC displaying the greatest distance to all others on average is depicted on the right. In a descending order, the CCs with successively smaller distances are arranged to the left.[58] As a result, we gain an ordered set of CCs, and the resulting surface plot changes, as shown in the upper-right part of Fig. 4.

The similarity of different CCs with regard to the dynamics of the statistical key figures is given when the DTW distance is small and tends toward zero. This is the case for CCs in the upper-left white corner in the sorted matrix. Starting from the top-left corner in the direction of the main diagonal up to a certain distance d_{bound}, the CCs thus delimited represent the market core of similar CCs.

Since the height profile above the sorted distance matrix has a peaked, rough structure, cf. Fig. I.6 in the appendix, the set of CCs belonging to the core cannot be delimited reliably. Therefore, modeling is carried out first, yielding a smoother height profile. We use a modeling method comparable to the analysis of hierarchical matrices, cf., e.g., Hackbusch (2015) and the corresponding literature cited therein.

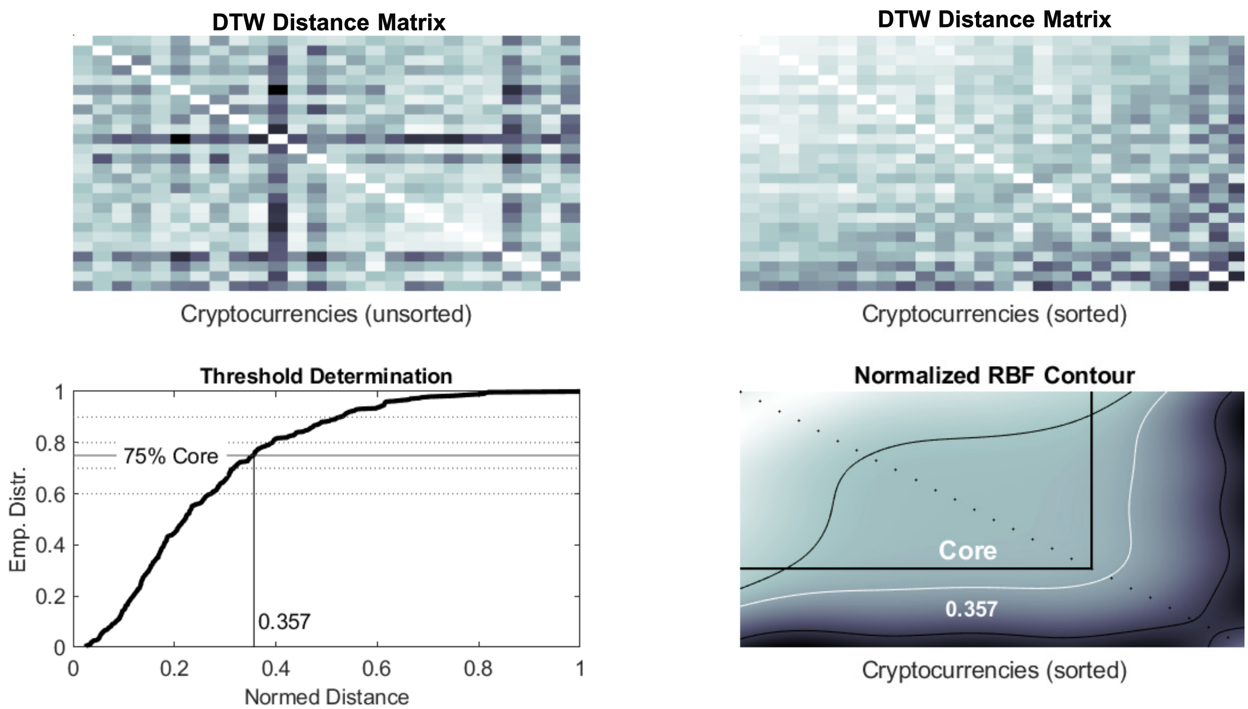
There is a certain basic structure of the matrix that simplifies the modeling problem. The sorted distance matrix is square, symmetrical and has only positive elements. The entries become larger on average toward the right and lower edge of the sorted distance matrix, essentially revealing a concave structure. In addition, we look only for a certain block in the sorted matrix, which starts in the upper-left corner and is itself square.

The surface's concave structure can be modeled well with RBFs, which have their center points—similar to a frame—in the outer area of the edges of the sorted distance matrix. A brief overview of the RBF model class used is given in I. If the individual elements of the distance matrix are

[58] This form of ordering is the same as sorting according to maximum rows or the column total.

normalized between 0 and 1, the modeling leads to an area whose height profile can be seen in the lower-right part of Fig. 4.

Figure 4: Core–Satellite Identification with DTW Distances for CCs



Shown is the procedure to identify and separate a core of some CCs within the whole market. The remaining CCs belong to a set that encloses the satellite. The DTW distances are based on the squared Euclidean metric.

In the next step, we define the boundary condition d_{bound}, which delimits the set of CCs belonging to the core. The distance matrix incorporates solely positive elements, but it is not positive definite in all cases; thus, some eigenvalues can be negative, and an analysis of the eigenvalue spectrum does not lead to the definition of a suitable threshold d_{bound}.

Instead of this consideration, we analyze the empirical distribution function over the elements of the upper triangular matrix normalized between 0 and 1 and delimit an area that contains p_{ed} percent of the smallest distances, cf. the lower-left part of Fig. 4. In practice, the p_{ed} value will be somewhere between 60% and 90% (dotted lines), where the steep slope of the empirical distribution function merges into the flatter area. This represents the tail area of the empirical distribution function in which the empirically measured DTW distances increase rapidly. If small values are found for d_{bound}, the associated core is more homogeneous. The larger the values are, the more heterogeneous the core becomes with regard to the statistical parameters. In our example, we find the inflection point at $p_{ed} \approx 75\%$. The associated threshold $d_{\text{bound}} = 0.357$ is used to draw a contour (white) in the modeled height profile on the right, which delimits an upper block matrix.

This block matrix describes the market core if the squared Euclidean metric is used. In Tab. 19, the penultimate column shows the CCs belonging to the core if this metric is utilized (a Boolean value of 1 indicates belonging to the core). In our analysis, we examine the DTW matrices for all

Table 19: Analysis of the DTW Distances for the Different Metrics

CC		**Name**	**Metric**			**Core**
No.	ID		Manh.	Eucl.	Sq. Eucl.	Intersection
		Threshold:	0.554	0.564	0.357	
1	ANC	Anoncoin	1	1	1	**C**
2	BTB	BitBar	1	1	1	**C**
3	BTC	Bitcoin	1	1	1	**C**
4	CSC	CasinoCoin	0	0	0	S
5	DEM	Deutsche eMark	1	1	1	**C**
6	DMD	Diamond	0	1	0	S
7	DGC	Digitalcoin	1	1	1	**C**
8	DOGE	Dogecoin	1	1	0	S
9	FTC	Feathercoin	1	1	1	**C**
10	FLO	FLO	1	1	1	**C**
11	FRC	Freicoin	0	0	0	S
12	GLC	GoldCoin	1	1	1	**C**
13	IFC	Infinitecoin	0	0	0	S
14	LTC	Litecoin	1	1	1	**C**
15	MEC	Megacoin	1	1	1	**C**
16	NMC	Namecoin	1	1	1	**C**
17	NVC	Novacoin	1	1	1	**C**
18	NXT	Nxt	1	1	1	**C**
19	OMNI	Omni	1	1	1	**C**
20	PPC	Peercoin	1	1	1	**C**
21	XPM	Primecoin	1	1	1	**C**
22	QRK	Quark	1	1	1	**C**
23	XRP	Ripple	0	0	0	S
24	TAG	TagCoin	1	1	0	S
25	TRC	Terracoin	1	1	1	**C**
26	WDC	WorldCoin	0	0	0	S
27	ZET	Zetacoin	1	1	1	**C**

Identification of the core (**C**) and the satellites (S). Threshold values are indicated for each distance metric.

metrics in the same way. The CCs belonging to the core according to the respective metric are shown in Tab. 19. Note that this method can also be used to find very similar CCs with almost the same statistical behavior if the lower inflection point is identified in the empirical distribution function and the bound d_{bound} is thus determined. We have also examined this path of segmentation (not explicitly shown here). This segmentation leads to the delimitation of five CCs in the white upper-left corner of the lower-right part in Fig. 4, which behave almost identically considering the statistical key figures over a long period of time.

Table 19 shows that the number of CCs belonging to the core depends on the metric. In portfolio management, it might be predicated on a decision of practicability regarding which metric to use and which dependency to accept. However, this dependency can be avoided by considering all metrics and selecting those CCs as the market core that are contained in the intersection of all metrics. This approach is illustrated in the last column of Tab. 19. In this column, all CCs belonging to the core according to all metrics are marked with **C**. This knowledge provides a decisive advantage in asset management when integrating a certain share of CCs in a portfolio.

Table 18 shows examples of CCs as representatives of the identified core CCs (XPM and ZET) and the identified satellite CCs (DMD and FRC). In practice, a simple portfolio could be constructed as follows. For example, 5–10 CCs with high liquidity and market depth similar to XPM/ZET that belong to the core are selected from the entire dataset. These CCs form the core investment. Individual CCs can then be selected from among the satellites, which can be expected to offer a higher return if the risk is higher. In the first case, the tracking error can be determined in relation to the core, and that in the second case can be determined in relation to the overall market. In any case, the composition is optimized taking a specified limitation of the tracking error into account. Continuous control of the tracking error and tactical readjustment of the weights leads to tracking of the core (first case) or the overall market (second case), whereby the tracking error specified by the institutional investor is followed.

4.6 Robustness

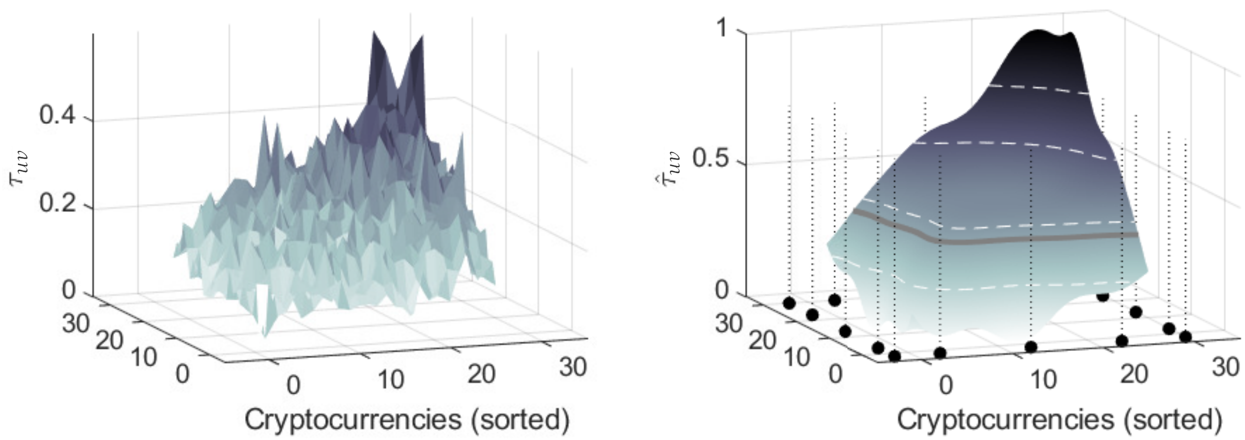
4.6.1 Core–Satellite Identification using Correlations

Our developed segmentation process takes into account the specifics of the CC market. This is achieved by explicitly considering the dynamics of the statistical parameters and by simultaneous utilizing the return, the standard deviation and especially the tail parameter.

Although correlation analysis is a common tool for determining similar and dissimilar assets (see, e.g., Heaney and Hooper (2001), Bekaert et al. (2011) and the corresponding literature cited therein), it is not possible to use several parameters simultaneously (e.g., the three-dimensional vector $(\langle r_{cc}\rangle, s_{cc}, \alpha)'$) and to consider their dynamics. This is exactly the problem: we lose important information that is necessary for the successful segmentation process, which we illustrate below.

At the beginning, we calculate the correlations of the returns over the entire period and end up with a 27×27 matrix. Here, we use Kendall's correlation coefficient because it is robust to a violation of the normal distribution assumption. Based on the correlation matrix, the steps of the segmentation process described in Sec. 4.5 are carried out. The unsorted and sorted correlation matrices (not shown here) entail the problem that the pairwise correlations with values of one are located on the diagonal. First, we perform the segmentation process without preprocessing the diagonals and find that no analysis is possible due to their highly peaked structure. Nevertheless, to enable carrying out the procedure, for the second step, we replace the entries on the diagonal by the mean values of the neighboring cells (a kind of presmoothing step). This at least succeeds in smoothing the peaked structure by the RBFs so that an evaluation is possible. Figure 5 shows the smoothing of the modified correlation matrix, with the correlations ranging from 0.0491 to 0.5981 in the left part, whereby they are normalized for modeling reasons in the right part. A brighter area indicates a lower correlation and vice versa.

Figure 5: Correlation and Normalized RBF Model



Critical step of the modeling process for the segmentation of the CC market using correlations.

Note that higher DTW distances are associated with greater dissimilarity, whereby a higher correlation indicates greater similarity. In this respect, the core of the CC market is now located in the corner opposite to the "DTW core", i.e., in the upper-right corner of the right part of Fig. 5. However, Fig. 5 clearly shows that the identification of a core is not possible at high correlations because no "plateau" of similar CCs emerges. Rather, the smoothed area falls continuously, so a suitable threshold d_{bound} cannot be reliably determined.

4.6.2 Return Correlations of the Core and Satellites

Another issue to be discussed comprises the correlations of CCs within the core, the correlations of CCs among the satellites and the potential differences between them. These correlations can provide important insights into whether the intended market segmentation has been achieved. Note that we analyze the correlations of the core and satellite CCs determined using our segmentation process with DTW distances.

Although we consider three parameters and their dynamics over six years and do not base the market segmentation on correlations, the correlations of the core CCs should be higher than those of the satellite CCs. This is the intended result, and it would provide evidence for successful market segmentation because we expect statistically homogeneous CCs in the core that are heterogeneous to the satellites.

While CCs are less correlated with traditional asset classes (Brière et al., 2015; Kuo Chuen et al., 2017; Liu and Tsyvinski, 2021), the correlation of CCs is more pronounced (Dorfleitner and Lung, 2018), which is also confirmed by our correlation analyses, as shown in Tab. 20.

Table 20: Correlation Analysis of the Entire Period

	CCs	Range	Mean	Median	Mean p value	Median p value
Complete	27	0.0491 – 0.5981	0.2223	0.2180	0.0227	0.0002
Core	19	0.0780 – 0.5981	0.2416	0.2308	0.0097	0.0001
Satellites	8	0.0491 – 0.3731	0.1751	0.1480	0.0638	0.0129

Kendall's correlation coefficient is used, and the calculated p values are based on a two-sided significance test.

For the whole sample, we report a range of correlations from 0.0491 to 0.5981 with a mean of 0.2223 and a median of 0.218. The average p value is 0.0227, and the median is 0.0002, which implies statistical significance at least at the 5% significance level.

With regard to considering the core and satellite CCs, the calculated correlations provide evidence for the intended segmentation of the CC market. The core CC correlations range from 0.078 to 0.5981 with a mean of 0.2416 and a median of 0.2308. The p value is 0.0097 on average and 0.0001 at the median, so it is statistically significant at least at the 1% significance level. In contrast, the correlations of the satellite CCs show a range from 0.0491 to 0.3731 with a mean of 0.1751 and a median of 0.148. The p value is 0.0638 at the mean and 0.0129 at the median, which indicates statistical significance at least at the 10% level. The initial assessment indicates a higher correlation range of CCs in the core compared to those among the satellites, which is our desired result.

Furthermore, we check whether the correlations between the core CCs differ significantly from those between the satellite CCs. This is accomplished by using Welch's parametric t test and the nonparametric Mann–Whitney U test. We perform one-sided tests because we assume the correlations between the core CCs are higher than those between the satellite CCs. The first test proves the null hypothesis that the means of the correlations of the core CCs and satellite CCs are equal, whereas the second test examines this for the central tendencies. The alternative hypothesis states that the mean or central tendencies of the correlations of the core CCs are higher than those of the satellite CCs. The respective null hypothesis is rejected at the 1% significance level for both tests, with a p value of 0.0007 for Welch's t-test and 0.0002 for the Mann–Whitney U test.

Thus, we can conclude that the correlations of the core CCs are higher than those of the satellite CCs. This finding provides evidence for the intended segmentation of the CC market.

4.7 Conclusion

In our study, we show how a general, purely data-driven process can be utilized successfully to separate an investment universe into similar assets (core) and dissimilar assets (satellites). We verify the feasibility of this approach and outline the necessary sequence of steps for the segmentation in detail. Using the example of the modern CC asset class, we separate the investment universe into similar CCs (core) and dissimilar CCs (satellites) as the residual share. In addition, we discern interesting results specifically concerning the CCs.

The results in Tab. 19 show that of the 27 CCs studied, 19 CCs belong to the core, whereas 8 CCs represent the satellites. The question raised at the beginning of whether Bitcoin actually represents the "hard core" of the CC market can be answered in a differentiated manner. It turns out that Bitcoin is part of the core, but not in its center. Recall that the threshold $d_{\text{bound}} = 0.357$ is used to draw a contour (white) in the modeled height profile on the lower-right part of Fig. 4, which delimits an upper block matrix. This block matrix represents the core of the CC market, wherein Bitcoin lies just inside and thus narrowly belongs to the core. Therefore, it is not part of the "hard core" of very similar CCs with low normalized DTW distances but is comparatively dissimilar to other core CCs. Thus, a dominant role within the CC market, as appears in other analyses, cannot be confirmed by our findings. Although our paper presents a methodological approach that aims to explain our proposed segmentation process, we nevertheless briefly discuss an exemplary use case of the results. In general, the market segmentation result can be used in portfolio management by institutional investors to track the core market with a few selected CCs in a tracking error approach, as described in more detail in Sec. 4.5. For example, 5–10 CCs of the core with high liquidity and market depth are selected to form the core investment. To increase returns, a higher-level management approach can then be used to build up individual positions in CCs that belong to the satellite, thus implementing a core–satellite portfolio.

One potential challenge for this approach might lie in liquidity problems, especially in the case of smaller altcoins (other than Bitcoin). However, studies indicate that CCs typically make up a smaller component of a portfolio of traditional assets, mitigating this issue (Dorfleitner and Lung, 2018; Schmitz and Hoffmann, 2020). In addition, methods such as the liquidity bounded risk–return optimization (LIBRO) approach by Trimborn et al. (2020) exist that can be used to optimize portfolios under liquidity constraints. Furthermore, it is conceivable that liquid CCs are incorporated into the core so that they can be purchased anyway without the fear of liquidity restrictions. Beyond that, it can be assumed that the development of the CC market will make it suitable for larger investment volumes in the future.

As already mentioned, the proposed method is not limited to CCs. A suitable market segmentation in other asset classes is conceivable, as well. The advantages of the product-based implementation of a topic-centered, combined "core–satellite & tracking-error" strategy in the private or institutional investor segment is reserved for further studies.

Title: Bitcoin: Like a Satellite or Always Hardcore? A Core–Satellite Identification in the Cryptocurrency Market

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Share of Contributions:

Contributions	Christoph J. Börner	Ingo Hoffmann	Jonas Krettek	Tim Schmitz
Research Design	30%	40%	0%	30%
Development of research question	30%	40%	0%	30%
Method development	30%	40%	0%	30%
Research performance & analysis	0%	20%	50%	30%
Literature Review and framework development	0%	40%	60%	0%
Data collection, preparation and analysis	0%	0%	10%	90%
Analysis and discussion of results	0%	20%	60%	20%
Derivation of implications and conclusions	0%	20%	70%	10%
Manuscript preparation	0%	0%	100%	0%
Final draft	0%	0%	100%	0%
Finalization	0%	0%	100%	0%
Overall contribution	10%	20%	50%	20%

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5 Concluding Remarks

This dissertation provides a comprehensive empirical analysis of three major developments that have shaped the banking sector over the past 20 years: (1) the extensive global post-GFC regulation of the three financial risks (market, credit, and liquidity) by the BCBS, (2) the drastic regime shift from a prolonged period of low interest rates to rapidly increasing policy rates by the Fed and the ECB, and (3) the gradual development of CCs into an independent asset class.

Accordingly, this dissertation addresses several pressing questions from the perspectives of banks and their key stakeholders. First, there is the question of how regulation and interest rate hikes affect bank shareholders and creditors—specifically, whether profitability and risk, as induced by these developments, have changed. These reactions also provide insight into whether the BCBS has achieved its regulatory objective of reducing bank risk. This is a particularly urgent issue for taxpayers globally, as governments around the world ultimately used public funds to bailout banks during the GFC. It is also crucial for central banks themselves to understand the extent to which their policy rate decisions influence capital markets. Regarding the topic of CCs, the key question from a banking perspective is how the CC market can be segmented for investment purposes, either for proprietary trading or within the context of asset management on behalf of clients.

Important implications for banking institutions and their stakeholders emerge from the three analyses presented in Sec. 2, Sec. 3, and Sec. 4, thereby contributing to the systematic answering of the pressing questions outlined above. Taken together, the three studies provide a multifaceted empirical foundation for understanding how regulatory interventions, monetary policy shifts, and new financial innovations impact bank profitability, bank risk, and strategic investment decisions. By integrating market-based methodologies with a cross-jurisdictional perspective and an approach to digital asset segmentation, this dissertation advances the empirical finance literature on systemic banking developments in the post-GFC era. The initial focus is on the results and implications of post-GFC regulation by the BCBS, as discussed in Sec. 2.

EU banks experienced significant negative stock market reactions in response to market and credit risk regulations. In contrast, U.S. banks showed no clear significant market responses, likely due to the earlier introduction of the Dodd-Frank Act and, in particular, more lenient regulatory enforcement. EU creditors reacted to credit risk regulation with a notable increase in CDS spreads, indicating heightened perceived risk as a result of reduced expectations of government bailouts. These findings suggest that the Basel reforms have been effective in shifting financial risk away from taxpayers and back to shareholders, and in curbing moral hazard among creditors. The pronounced divergence in market reactions between the EU and the U.S. raises concerns about an uneven regulatory landscape. While the BCBS has made progress in reducing bailout probabilities through financial risk regulation, these discrepancies underscore the need for more consistent implementation. Without it, market confidence in a level playing field may erode.

The second analysis in Sec. 3 aims to examine the effects of interest rate hikes by the Fed and the ECB on shareholders and creditors of banks and insurance companies in the U.S. and the Eurozone. Unlike the study referenced in Sec. 2, the European sample focuses not on EU-wide firms, but specifically on firms based in the Eurozone. This restriction is appropriate, as it ensures that the banks and insurers considered operate in a common currency environment—the euro. This study provides valuable insights into the consequences of contractionary monetary policy in the two most important economic regions after years of historically low interest rates. The analysis enables conclusions about the impact on the earnings capacity and risk exposure of financial intermediaries. Furthermore, it enables the examination of spillover effects from ECB and Fed policy on shareholders and creditors of financial intermediaries in the respective other region, offering important and novel findings.

In this context, empirical evidence demonstrates that interest rate increases by the Fed and the ECB, when surpassing expectations, reduce domestic stock valuations and widen CDS spreads. Cross-border effects are also significant, though asymmetric in nature: Eurozone stocks respond positively to Fed tightening, likely driven by relative valuation effects and capital inflows from the U.S. to the Eurozone. For creditors of Eurozone institutions, CDS spreads also rise, which is attributable to the fact that the CDS portfolios consist exclusively of large, cross-border financial institutions. In response to ECB policy actions, U.S. shareholders show significant but directionally mixed reactions. In contrast, U.S. creditors exhibit clearer signs of heightened risk perception, as evidenced by rising CDS spreads. The ambiguous stock market response in the U.S. to ECB measures may be explained by the country's market-oriented financial system, which, compared to Europe, features a higher share of small, publicly listed financial intermediaries operating at the local level—particularly in the bank portfolio.

As previously discussed, CCs have established themselves as a distinct asset class since the launch of Bitcoin in 2008. For banks, it is crucial to segment this evolving market systematically to identify and seize emerging opportunities. In Sec. 4, a tool is developed to segment the CC market, supporting banks in making sound investment decisions. This tool offers two essential advantages: first, it captures the dynamic nature of the CC market's development by analyzing the statistical properties of CCs using the DTW algorithm; second, it explicitly accounts for the statistical distribution of returns, particularly the presence of heavy tails.

Limitations in the first two empirical analyses in Sec. 2 and Sec. 3 primarily arise from the event study methodology itself. The econometric analysis of stock and CDS markets allows for the identification of changes in earnings capacity and risk profile as perceived by market participants in response to the respective events. This approach is particularly appealing because asset prices immediately reflect market expectations given semi-strong informational efficiency, whereas reliable direct measures of actual profitability and risk—especially in the context of regulatory impacts or central bank rate hikes—would require several years of post-event data and observation. Although the event study methodology is well-established and delivers robust results under careful application, the findings presented here should be regarded as a starting point for further research. In particular, future studies could build on these market-based insights by examining how regulation and monetary policy affect the actual balance sheet risk and profitability of banks over longer time horizons. This is particularly important, as market behavior may not always be fully rational, and short-term price reactions might fail to capture the true underlying economic fundamentals.

Beyond the current scope, the two studies focusing on the U.S. and Europe could be further expanded. With regard to the analysis of post-GFC regulation, it would be particularly relevant from the perspective of the BCBS to examine whether differences in the strictness of regulatory implementation across additional jurisdictions also result in divergent market reactions. Japan and selected emerging market economies could serve as illustrative cases. In the context of interest rate policy, a key contribution lies in the analysis of spillover effects from one central bank into the financial markets of other jurisdictions. Future empirical research could build on this and investigate whether similar effects of Fed and ECB policy actions are observable in markets beyond the U.S. and Europe.

Certain limitations and avenues for future research also exist with regard to the segmentation approach developed for the CC market in Sec. 4. An essential component of the proposed approach is the explicit incorporation of the tails of CC return distributions into the segmentation process. This allows for a distinction between CCs with more pronounced and less pronounced tail behavior. While existing research provides empirical support for modeling CCs in the tails using the SDI, it is generally advisable to reassess this with newly available CC return data. As emphasized throughout this dissertation, the CC market is continuously evolving. It is therefore conceivable that, over time, the statistical properties of CCs may converge toward those of more established asset classes. Moreover, the presented core–satellite approach could be applied to other asset classes as well. Naturally, the characteristics relevant to the respective asset class would then have to be identified through pertinent literature and the author's own statistical analyses.

For regulators, policymakers and central banks, the findings of this dissertation highlight the need for consistent international regulatory implementation and for close monitoring of how interest rate changes affect the profitability and risk profile of financial intermediaries. This also applies to institutions in other jurisdictions, as central bank decisions can generate significant cross-border spillover effects. These insights are particularly relevant for financial market stability, especially given the presence of multiple contagion channels. In addition to the implications for traditional financial intermediaries, the core–satellite approach introduced in this dissertation also yields important regulatory insights. While it offers a practice-oriented segmentation of the CC market from an investor's perspective, its findings are equally relevant for regulators. As the global regulatory framework for CCs remains fragmented and underdeveloped, the potential involvement of banks—such as through proprietary trading—raises key questions about risk measurement and capital requirements. The segmentation framework can support regulatory efforts by showing that statistically similar behavior is concentrated in the core segment of the market, potentially indicating concentration risks that require closer regulatory scrutiny and could have implications for risk-weighted capital requirements. For practitioners, particularly in banking and asset management, the framework also serves as a novel tool for navigating the evolving and volatile crypto market, enabling more informed portfolio decisions. As the banking system continues to undergo rapid transformation through evolving regulation, shifting macroeconomic dynamics, and technological innovation, a deeper empirical understanding of these developments becomes increasingly vital.

In sum, this dissertation provides empirically grounded insights and actionable tools that support banks and their stakeholders in navigating an increasingly complex and interconnected financial system.

References

Acharya, S., 1996. Charter value, minimum bank capital requirement and deposit insurance pricing in equilibrium. Journal of Banking & Finance 20, 351–375. doi:10.1016/0378-4266(94)00126-X.

Acharya, V., Drechsler, I., Schnabl, P., 2014. A pyrrhic victory? bank bailouts and sovereign credit risk. The Journal of Finance 69, 2689–2739. doi:10.1111/jofi.12206.

Acosta, M., Brennan, C.M., Jacobson, M.M., 2024. Constructing high-frequency monetary policy surprises from sofr futures. Economics Letters 242, 111873. doi:10.1016/j.econlet.2024.111873.

Aghabozorgi, S., Seyed Shirkhorshidi, A., Ying Wah, T., 2015. Time-series clustering – a decade review. Information Systems 53, 16–38. doi:10.1016/j.is.2015.04.007.

Aharony, J., Saunders, A., Swary, I., 1986. The effects of a shift in monetary policy regime on the profitability and risk of commercial banks. Journal of Monetary Economics 17, 363–377. doi:10.1016/0304-3932(86)90063-2.

Aït-Sahalia, Y., Andritzky, J., Jobst, A., Nowak, S., Tamirisa, N., 2012. Market response to policy initiatives during the global financial crisis. Journal of International Economics 87, 162–177. doi:10.1016/j.jinteco.2011.12.001.

Akella, S.R., Greenbaum, S.I., 1992. Innovations in interest rates, duration transformation, and bank stock returns. Journal of Money, Credit and Banking 24, 27–42. doi:10.2307/1992789.

Albertazzi, U., Gambacorta, L., 2009. Bank profitability and the business cycle. Journal of Financial Stability 5, 393–409. doi:10.1016/j.jfs.2008.10.002.

Allen, P.R., Wilhelm, W.J., 1988. The impact of the 1980 depository institutions deregulation and monetary control act on market value and risk: Evidence from the capital markets. Journal of Money, Credit and Banking 20, 364–380. doi:10.2307/1992262.

Altavilla, C., Brugnolini, L., Gürkaynak, R.S., Motto, R., Ragusa, G., 2019. Measuring euro area monetary policy. Journal of Monetary Economics 108, 162–179. doi:10.1016/j.jmoneco.2019.08.016.

Amenc, N., Malaise, P., Martellini, L., 2012. Revisiting core-satellite investing - a dynamic model of relative risk management. URL: https://climateinstitute.edhec.edu/publications/revisiting-core-satellite-investing-dynamic-model-relative-risk-management.

Ammer, J., Vega, C., Wongswan, J., 2010. International transmission of u.s. monetary policy shocks: Evidence from stock prices. Journal of Money, Credit and Banking 42, 179–198. doi:10.1111/j.1538-4616.2010.00333.x.

Andres, C., Betzer, A., Doumet, M., 2021. Measuring changes in credit risk: The case of cds event studies. Global Finance Journal 49, 100647. doi:10.1016/j.gfj.2021.100647.

Angeloni, I., Ehrmann, M., 2003. Monetary transmission in the euro area: early evidence. Economic Policy 18, 469–501. URL: https://www.jstor.org/stable/1344742.

Armstrong, C.S., Barth, M.E., Jagolinzer, A.D., Riedl, E.J., 2010. Market reaction to the adoption of ifrs in europe. The Accounting Review 85, 31–61. doi:10.2308/accr.2010.85.1.31.

Aslanidis, N., Bariviera, A.F., Savva, C.S., 2020. Weekly dynamic conditional correlations among cryptocurrencies and traditional assets. SSRN Electronic Journal. doi:10.2139/ssrn.3550879.

Balcilar, M., Bouri, E., Gupta, R., Roubaud, D., 2017. Can volume predict bitcoin returns and volatility? a quantiles-based approach. Economic Modelling 64, 74–81. doi:10.1016/J.ECONMOD.2017.03.019.

Ball, R., Brown, P., 1968. An empirical evaluation of accounting income numbers. Journal of Accounting Research 6, 159–178. doi:10.2307/2490232.

Bariviera, A.F., Basgall, M.J., Hasperué, W., Naiouf, M., 2017. Some stylized facts of the bitcoin market. Physica A: Statistical Mechanics and its Applications 484, 82–90. doi:10.1016/j.physa.2017.04.159.

Barth, J.R., Miller, S.M., 2018. Benefits and costs of a higher bank "leverage ratio". Journal of Financial Stability 38, 37–52. doi:10.1016/j.jfs.2018.07.001.

Basel Committee on Banking Supervision, 1988. International convergence of capital measurement and capital standards. URL: https://www.bis.org/publ/bcbs04a.pdf.

Basel Committee on Banking Supervision, 1996. Amendment to the capital accord to incorporate market risks. URL: https://www.bis.org/publ/bcbs24.pdf.

Basel Committee on Banking Supervision, 2004. International convergence of capital measurement and capital standards. a revised framework. URL: https://www.bis.org/publ/bcbs107.pdf.

Basel Committee on Banking Supervision, 2011. Basel iii: a global regulatory framework for more resilient banks and banking systems. December 2010 (revised June 2011). URL: http://www.bis.org/publ/bcbs189.pdf.

Basel Committee on Banking Supervision, 2012. Basel iii regulatory consistency assessment (level 2): Preliminary report: United states of america. URL: https://www.bis.org/bcbs/implementation/l2_us.pdf.

Basel Committee on Banking Supervision, 2013. Basel iii: The liquidity coverage ratio and liquidity risk monitoring tools. URL: https://www.bis.org/publ/bcbs238.pdf.

Basel Committee on Banking Supervision, 2014a. Basel iii: the net stable funding ratio. URL: https://www.bis.org/bcbs/publ/d295.pdf.

Basel Committee on Banking Supervision, 2014b. Liquidity coverage ratio disclosure standards. January 2014 (revised March 2014). URL: https://www.bis.org/publ/bcbs272.pdf.

Basel Committee on Banking Supervision, 2014c. Regulatory consistency assessment programme (rcap): Assessment of basel iii regulations - united states of america. URL: https://www.bis.org/bcbs/publ/d301.pdf.

Basel Committee on Banking Supervision, 2015. Net stable funding ratio disclosure standards. URL: https://www.bis.org/bcbs/publ/d324.pdf.

Basel Committee on Banking Supervision, 2017. The regulatory treatment of sovereign exposures. Discussion Paper. URL: https://www.bis.org/bcbs/publ/d425.pdf.

Basel Committee on Banking Supervision, 2019. The costs and benefits of bank capital - a review of the literature. Working Paper 37. URL: https://www.bis.org/bcbs/publ/wp37.pdf.

Basel Committee on Banking Supervision, 2022. Regulatory consistency assessment programme (rcap): Assessment of basel nsfr regulations - european union. URL: https://www.bis.org/bcbs/publ/d535.pdf.

Basel Committee on Banking Supervision, 2025. Basel committee membership. Last accessed on July 8, 2025. URL: https://www.bis.org/bcbs/membership.htm.

Baselga-Pascual, L., Trujillo-Ponce, A., Cardone-Riportella, C., 2015. Factors influencing bank risk in europe: Evidence from the financial crisis. The North American Journal of Economics and Finance 34, 138–166. doi:10.1016/j.najef.2015.08.004.

Bats, J.V., Giuliodori, M., Houben, A.C., 2023. Monetary policy effects in times of negative interest rates: What do bank stock prices tell us? Journal of Financial Intermediation 53, 101003. doi:10.1016/j.jfi.2022.101003.

Baumgärtner, M., 2020. Information shocks and uncertainty. Working Paper. doi:10.13140/RG.2.2.22504.19201.

Baur, D.G., Hong, K., Lee, A.D., 2018. Bitcoin: Medium of exchange or speculative assets? Journal of International Financial Markets, Institutions and Money 54, 177–189. doi:10.1016/j.intfin.2017.12.004.

Becker, B., Ivashina, V., 2015. Reaching for yield in the bond market. The Journal of Finance 70, 1863–1902. doi:10.1111/jofi.12199.

Becker, B., Opp, M.M., Saidi, F., 2022. Regulatory forbearance in the u.s. insurance industry: The effects of removing capital requirements for an asset class. Review of Financial Studies 35, 5438–5482. doi:10.1093/rfs/hhab102.

Bekaert, G., Harvey, C.R., Lundblad, C.T., Siegel, S., 2011. What segments equity markets? Review of Financial Studies 24, 3841–3890. doi:10.1093/rfs/hhr082.

Berger, A.N., Bouwman, C.H., 2013. How does capital affect bank performance during financial crises? Journal of Financial Economics 109, 146–176. doi:10.1016/j.jfineco.2013.02.008.

Bernanke, B.S., Blinder, A.S., 1988. Credit, money, and aggregate demand. The American Economic Review 78, 435–439. URL: https://www.jstor.org/stable/1818164.

Bernanke, B.S., Gertler, M., 1989. Agency costs, net worth, and business fluctuations. The American Economic Review 79, 14–31. URL: https://www.jstor.org/stable/1804770.

Bernanke, B.S., Gertler, M., Gilchrist, S., 1996. The financial accelerator and the flight to quality. The Review of Economics and Statistics 78, 1–15. URL: https://www.jstor.org/stable/2109844.

Bernanke, B.S., Kuttner, K.N., 2005. What explains the stock market's reaction to federal reserve policy? The Journal of Finance 60, 1221–1257. doi:10.1111/j.1540-6261.2005.00760.x.

Bessembinder, H., Kahle, K.M., Maxwell, W.F., Xu, D., 2009. Measuring abnormal bond performance. Review of Financial Studies 22, 4219–4258. doi:10.1093/rfs/hhn105.

Bey, R.P., 1983. Market model stationarity of individual public utilities. Journal of Financial and Quantitative Analysis 18, 67. doi:10.2307/2330805.

Bhargava, R., Fraser, D.R., 1998. On the wealth and risk effects of commercial bank expansion into securities underwriting: An analysis of section 20 subsidiaries. Journal of Banking & Finance 22, 447–465. doi:10.1016/S0378-4266(98)00022-3.

Biancolini, M.E., 2017. Fast Radial Basis Functions for Engineering Applications. Springer, Cham. doi:10.1007/978-3-319-75011-8.

Binder, J., 1998. The event study methodology since 1969. Review of Quantitative Finance and Accounting 11, 111–137. doi:10.1023/A:1008295500105.

Binder, J.J., 1985a. Measuring the effects of regulation with stock price data. The RAND Journal of Economics 16, 167–183. URL: https://www.jstor.org/stable/2555408.

Binder, J.J., 1985b. On the use of the multivariate regression model in event studies. Journal of Accounting Research 23, 370–383. URL: https://www.jstor.org/stable/2490925.

Blaško, M., Sinkey Jr., J.F., 2006. Bank asset structure, real-estate lending, and risk-taking. The Quarterly Review of Economics and Finance 46, 53–81. doi:10.1016/j.qref.2004.11.002.

Boehmer, E., Masumeci, J., Poulsen, A.B., 1991. Event-study methodology under conditions of event-induced variance. Journal of Financial Economics 30, 253–272. doi:10.1016/0304-405X(91)90032-F.

Bolt, W., de Haan, L., Hoeberichts, M., van Oordt, M.R., Swank, J., 2012. Bank profitability during recessions. Journal of Banking & Finance 36, 2552–2564. doi:10.1016/j.jbankfin.2012.05.011.

Bomfim, A.N., 2003. Pre-announcement effects, news effects, and volatility: Monetary policy and the stock market. Journal of Banking & Finance 27, 133–151. doi:10.1016/S0378-4266(01)00211-4.

Börner, C.J., Hoffmann, I., Kürzinger, L.M., Schmitz, T., 2025. On the return distributions of a basket of cryptocurrencies and subsequent implications. Research in Economics 79, 101028. doi:10.1016/j.rie.2025.101028.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., Hagfors, L.I., 2017. On the hedge and safe haven properties of bitcoin: Is it really more than a diversifier? Finance Research Letters 20, 192–198. doi:10.1016/j.frl.2016.09.025.

Boyd, J.H., Hu, J., Jagannathan, R., 2005. The stock market's reaction to unemployment news: Why bad news is usually good for stocks. The Journal of Finance 60, 649–672. doi:10.1111/j.1540-6261.2005.00742.x.

Brauneis, A., Mestel, R., 2018. Price discovery of cryptocurrencies: Bitcoin and beyond. Economics Letters 165, 58–61. doi:10.1016/j.econlet.2018.02.001.

Brewer, E., Carson, J.M., Elyasiani, E., Mansur, I., Scott, W.L., 2007. Interest rate risk and equity values of life insurance companies: A garch–m model. The Journal of Risk and Insurance 74, 401–423. doi:10.1111/j.1539-6975.2007.00218.x.

Brière, M., Oosterlinck, K., Szafarz, A., 2015. Virtual currency, tangible return: Portfolio diversification with bitcoin. Journal of Asset Management 16, 365–373. doi:10.1057/jam.2015.5.

Brissimis, S.N., Delis, M.D., Papanikolaou, N.I., 2008. Exploring the nexus between banking sector reform and performance: Evidence from newly acceded eu countries. Journal of Banking & Finance 32, 2674–2683. doi:10.1016/j.jbankfin.2008.07.002.

Brook, Y., Hendershott, R., Lee, D., 1998. The gains from takeover deregulation: Evidence from the end of interstate banking restrictions. The Journal of Finance 53, 2185–2204. doi:10.1111/0022-1082.00087.

Brown, S.J., Warner, J.B., 1985. Using daily stock returns: The case of event studies. Journal of Financial Economics 14, 3–31. doi:10.1016/0304-405X(85)90042-X.

Bruno, B., Onali, E., Schaeck, K., 2018. Market reaction to bank liquidity regulation. Journal of Financial and Quantitative Analysis 53, 899–935. doi:10.1017/S0022109017001089.

Busch, R., Memmel, C., 2017. Banks' net interest margin and the level of interest rates. Credit and Capital Markets – Kredit und Kapital 50, 363–392. doi:10.3790/ccm.50.3.363.

Campbell, C.J., Wesley, C.E., 1993. Measuring security price performance using daily nasdaq returns. Journal of Financial Economics 33, 73–92. doi:10.1016/0304-405X(93)90025-7.

Campbell, J.Y., Lo, A.W., MacKinlay, A.C., 1997. The econometrics of financial markets. 2. printing, with corrections ed., Princeton Univ. Press, Princeton, NJ.

Caporale, G.M., Gil-Alana, L., Plastun, A., 2018. Persistence in the cryptocurrency market. Research in International Business and Finance 46, 141–148. doi:10.1016/j.ribaf.2018.01.002.

Carboni, M., Fiordelisi, F., Ricci, O., Lopes, F.S.S., 2017. Surprised or not surprised? the investors' reaction to the comprehensive assessment preceding the launch of the banking union. Journal of Banking & Finance 74, 122–132. doi:10.1016/j.jbankfin.2016.11.004.

Carow, K.A., Heron, R.A., 1998. The interstate banking and branching efficiency act of 1994: A wealth event for acquisition targets. Journal of Banking & Finance 22, 175–196. doi:10.1016/S0378-4266(97)00052-6.

Cheah, E.T., Fry, J., 2015. Speculative bubbles in bitcoin markets? an empirical investigation into the fundamental value of bitcoin. Economics Letters 130, 32–36. doi:10.1016/j.econlet.2015.02.029.

Chuliá, H., Martens, M., van Dijk, D., 2010. Asymmetric effects of federal funds target rate changes on s&p100 stock returns, volatilities and correlations. Journal of Banking & Finance 34, 834–839. doi:10.1016/j.jbankfin.2009.09.012.

CoinMarketCap, 2025. Crypto market overview. Last accessed on July 8, 2025. URL: https://coinmarketcap.com/charts/.

Collin-Dufresne, P., Goldstein, R.S., Martin, J.S., 2001. The determinants of credit spread changes. The Journal of Finance 56, 2177–2207. doi:10.1111/0022-1082.00402.

Conover, C., Jensen, G.R., Johnson, R.R., 1999. Monetary environments and international stock returns. Journal of Banking & Finance 23, 1357–1381. doi:10.1016/S0378-4266(99)00007-2.

Cook, T., Hahn, T., 1989. The effect of changes in the federal funds rate target on market interest rates in the 1970s. Journal of Monetary Economics 24, 331–351. doi:10.1016/0304-3932(89)90025-1.

Cooper, K., Kolari, J., Wagster, J., 1991. A note on the stock market effects of the adoption of risk-based capital requirements on international banks in different countries. Journal of Banking & Finance 15, 367–381. doi:10.1016/0378-4266(91)90073-U.

Corbet, S., Lucey, B., Yarovaya, L., 2018a. Datestamping the bitcoin and ethereum bubbles. Finance Research Letters 26, 81–88. doi:10.1016/j.frl.2017.12.006.

Corbet, S., Meegan, A., Larkin, C., Lucey, B., Yarovaya, L., 2018b. Exploring the dynamic relationships between cryptocurrencies and other financial assets. Economics Letters 165, 28–34. doi:10.1016/j.econlet.2018.01.004.

Cornett, M.M., Tehranian, H., 1989. Stock market reactions to the depository institutions deregulation and monetary control act of 1980. Journal of Banking & Finance 13, 81–100. doi:10.1016/0378-4266(89)90021-6.

Cornett, M.M., Tehranian, H., 1990. An examination of the impact of the garn-st. germain depository institutions act of 1982 on commercial banks and savings and loans. The Journal of Finance 45, 95–111. doi:10.2307/2328811.

Corrado, C.J., 1989. A nonparametric test for abnormal security-price performance in event studies. Journal of Financial Economics 23, 385–395. doi:10.1016/0304-405X(89)90064-0.

Corrado, C.J., Zivney, T.L., 1992. The specification and power of the sign test in event study hypothesis tests using daily stock returns. Journal of Financial and Quantitative Analysis 27, 465–478. doi:10.2307/2331331.

Couaillier, C., Henricot, D., 2023. How do markets react to tighter bank capital requirements? Journal of Banking & Finance 151, 106832. doi:10.1016/j.jbankfin.2023.106832.

Crowder, W.J., 2006. The interaction of monetary policy and stock returns. Journal of Financial Research 29, 523–535. doi:10.1111/j.1475-6803.2006.00192.x.

Czaja, M.G., Scholz, H., Wilkens, M., 2009. Interest rate risk of german financial institutions: the impact of level, slope, and curvature of the term structure. Review of Quantitative Finance and Accounting 33, 1–26. doi:10.1007/s11156-008-0104-9.

Dann, L.Y., James, C.M., 1982. An analysis of the impact of deposit rate ceilings on the market values of thrift institutions. The Journal of Finance 37, 1259–1275. doi:10.2307/2327849.

Dechow, P.M., Kothari, S.P., L. Watts, R., 1998. The relation between earnings and cash flows. Journal of Accounting and Economics 25, 133–168. doi:10.1016/S0165-4101(98)00020-2.

Deutsche Bundesbank, 2023. Developments in bank interest rates in germany during the period of monetary policy tightening. Monthly Report June 2023 75, 39–62. URL: https://www.bundesbank.de/resource/blob/724440/4e2554c5cc91e6ded1ab2ccc6dc89717/472B63F073F071307366337C94F8C870/2023-06-monatsbericht-data.pdf.

Dierick, F., Pires, F., Scheicher, M., Spitzer, K.G., 2005. The new basel capital framework and its implementation in the european union. ECB Occasional Paper Series No. 42 / December 2005 URL: https://www.ecb.europa.eu/pub/pdf/scpops/ecbocp42.pdf.

Dietrich, A., Hess, K., Wanzenried, G., 2014. The good and bad news about the new liquidity rules of basel iii in western european countries. Journal of Banking & Finance 44, 13–25. doi:10.1016/j.jbankfin.2014.03.041.

Dorfleitner, G., Lung, C., 2018. Cryptocurrencies from the perspective of euro investors: a re-examination of diversification benefits and a new day-of-the-week effect. Journal of Asset Management 19, 472–494. doi:10.1057/s41260-018-0093-8.

Doukakis, L., Ghicas, D.C., Siougle, G., Sougiannis, T., 2020. The informativeness of micro and macro information during economic crisis and non-crisis periods: Evidence from europe. European Accounting Review 29, 467–492. doi:10.1080/09638180.2019.1642221.

Dräger, V., Heckmann-Draisbach, L., Memmel, C., 2021. Interest and credit risk management in german banks. German Economic Review 22, 63–95. doi:10.1515/ger-2019-0114.

Dwyer, G.P., 2015. The economics of bitcoin and similar private digital currencies. Journal of Financial Stability 17, 81–91. doi:10.1016/j.jfs.2014.11.006.

Ehrmann, M., Fratzscher, M., 2004. Taking stock: Monetary policy transmission to equity markets. Journal of Money, Credit and Banking 36, 719–737. URL: https://www.jstor.org/stable/3839039.

ElBahrawy, A., Alessandretti, L., Kandler, A., Pastor-Satorras, R., Baronchelli, A., 2017. Evolutionary dynamics of the cryptocurrency market. Royal Society open science 4, 170623. doi:10.1098/rsos.170623.

English, W.B., van den Heuvel, S.J., Zakrajšek, E., 2018. Interest rate risk and bank equity valuations. Journal of Monetary Economics 98, 80–97. doi:10.1016/j.jmoneco.2018.04.010.

Ericsson, J., Jacobs, K., Oviedo, R., 2009. The determinants of credit default swap premia. Journal of Financial and Quantitative Analysis 44, 109–132. doi:10.1017/s0022109009090061.

European Banking Authority, 2012. Results of the basel iii monitoring exercise based on data as of 31 december 2011. URL: https://www.eba.europa.eu/documents/10180/16145/557ba16e-232d-4b30-a414-dbd144d88e2b/EBA-BS-2012-xxx--Public-ISG-Report-Basel-III-Monitoring-.pdf.

European Securities and Markets Authority, 2023. List of market makers and authorised primary dealers who are using the exemption under the regulation on short selling and credit default swaps. Version used: last update April 14, 2023. URL: https://www.esma.europa.eu/sites/default/files/library/list_of_market_makers_and_primary_dealers.pdf.

Eyssell, T., Arshadi, N., 1990. The wealth effects of the risk-based capital requirement in banking: The evidence from the capital market. Journal of Banking & Finance 14, 179–197. doi:10.1016/0378-4266(90)90043-2.

Fama, E.F., 1970. Efficient capital markets: A review of theory and empirical work. The Journal of Finance 25, 383–417. doi:10.2307/2325486.

Fama, E.F., Fisher, L., Jensen, M.C., Roll, R., 1969. The adjustment of stock prices to new information. International Economic Review 10, 1–21. doi:10.2307/2525569.

Fama, E.F., French, K.R., 2006. Profitability, investment and average returns. Journal of Financial Economics 82, 491–518. doi:10.1016/j.jfineco.2005.09.009.

Farruggio, C., Michalak, T.C., Uhde, A., 2013. The light and dark side of tarp. Journal of Banking & Finance 37, 2586–2604. doi:10.1016/j.jbankfin.2013.02.020.

Federal Financial Supervisory Authority, 2023. Life insurers: when interest rates rise. Last accessed on July 8, 2025. URL: https://www.bafin.de/SharedDocs/Veroeffentlichungen/EN/Fachartikel/2023/fa_bj_2304_Lebensversicherer_Wenn_Zinsen_steigen_en.html.

Fiordelisi, F., Galloppo, G., Ricci, O., 2014. The effect of monetary policy interventions on interbank markets, equity indices and g-sifis during financial crisis. Journal of Financial Stability 11, 49–61. doi:10.1016/j.jfs.2013.12.002.

Fiordelisi, F., Molyneux, P., 2010. The determinants of shareholder value in european banking. Journal of Banking & Finance 34, 1189–1200. doi:10.1016/j.jbankfin.2009.11.018.

Fiordelisi, F., Ricci, O., 2016. "whatever it takes": An empirical assessment of the value of policy actions in banking. Review of Finance 20, 2321–2347. doi:10.1093/rof/rfv053.

Fiordelisi, F., Ricci, O., Stentella Lopes, F.S., 2017. The unintended consequences of the launch of the single supervisory mechanism in europe. Journal of Financial and Quantitative Analysis 52, 2809–2836. doi:10.1017/S0022109017000886.

Flannery, M.J., James, C.M., 1984. The effect of interest rate changes on the common stock returns of financial institutions. The Journal of Finance 39, 1141–1153. doi:10.1111/j.1540-6261.1984.tb03898.x.

French, K.R., Ruback, R.S., Schwert, G.W., 1983. Effects of nominal contracting on stock returns. Journal of Political Economy 91, 70–96. doi:10.1086/261129.

Fry, J., Cheah, E.T., 2016. Negative bubbles and shocks in cryptocurrency markets. International Review of Financial Analysis 47, 343–352. doi:10.1016/j.irfa.2016.02.008.

Fuller, K., Netter, J., Stegemoller, M., 2002. What do returns to acquiring firms tell us? evidence from firms that make many acquisitions. The Journal of Finance 57, 1763–1793. doi:10.1111/1540-6261.00477.

Gandal, N., Hamrick, J.T., Moore, T., Oberman, T., 2018. Price manipulation in the bitcoin ecosystem. Journal of Monetary Economics 95, 86–96. doi:10.1016/j.jmoneco.2017.12.004.

Gennaioli, N., Martin, A., Rossi, S., 2018. Banks, government bonds, and default: What do the data say? Journal of Monetary Economics 98, 98–113. doi:10.1016/j.jmoneco.2018.04.011.

Giorgino, T., 2009. Computing and visualizing dynamic time warping alignments in r : The dtw package. Journal of Statistical Software 31, 1–24. doi:10.18637/jss.v031.i07.

Gkillas, K., Bekiros, S., Siriopoulos, C., 2018. Extreme correlation in cryptocurrency markets. SSRN Electronic Journal. doi:10.2139/ssrn.3180934.

Gkillas, K., Katsiampa, P., 2018. An application of extreme value theory to cryptocurrencies. Economics Letters 164, 109–111. doi:10.1016/j.econlet.2018.01.020.

Glas, T.N., 2019. Investments in cryptocurrencies: Handle with care! The Journal of Alternative Investments 22, 96–113. doi:10.3905/jai.2019.22.1.096.

Glaser, F., Zimmermann, K., Haferkorn, M., Weber, M.C., Siering, M., 2014. Bitcoin - asset or currency? revealing users' hidden intentions. ECIS 2014 (Tel Aviv). URL: https://ssrn.com/abstract=2425247.

Goyal, V.K., 2005. Market discipline of bank risk: Evidence from subordinated debt contracts. Journal of Financial Intermediation 14, 318–350. doi:10.1016/j.jfi.2004.06.002.

Greenwood, R., Landier, A., Thesmar, D., 2015. Vulnerable banks. Journal of Financial Economics 115, 471–485. doi:10.1016/j.jfineco.2014.11.006.

Groba, J., Serrano, P., 2020. Foreign monetary policy and firms' default risk. The European Journal of Finance 26, 1047–1074. doi:10.1080/1351847X.2019.1710225.

Gürkaynak, R.S., Sack, B., Swanson, E.T., 2005. Do actions speak louder than words? the response of asset prices to monetary policy actions and statements. International Journal of Central Banking 1, 55–93. URL: https://www.ijcb.org/journal/ijcb05q2a2.pdf.

Hackbusch, W., 2015. Hierarchical matrices: Algorithms and analysis. volume 49 of *Springer Series in Computational Mathematics*. Springer, Heidelberg and New York and Dordrecht and London.

Hausman, J., Wongswan, J., 2011. Global asset prices and fomc announcements. Journal of International Money and Finance 30, 547–571. doi:10.1016/j.jimonfin.2011.01.008.

Hayes, A.S., 2017. Cryptocurrency value formation: An empirical study leading to a cost of production model for valuing bitcoin. Telematics & Informatics 34, 1308–1321. doi:10.1016/j.tele.2016.05.005.

Heaney, R., Hooper, V., 2001. Regionalism, political risk and capital market segmentation in international asset pricing. Journal of Economic Integration 16, 299–312. doi:10.11130/jei.2001.16.3.299.

Hippert, B., Uhde, A., 2021. Cds investors' risk perceptions of m&a announcements. SSRN Electronic Journal. doi:10.2139/ssrn.3822523.

Hobelsberger, K., Kok, C., Mongelli, F.P., 2022. A tale of three crises: Synergies between ecb tasks. ECB Occasional Paper Series No. 305 / September 2022 (revised June 2023). URL: https://www.ecb.europa.eu/pub/pdf/scpops/ecb.op305~f9d43bd762.en.pdf.

Hoggarth, G., Sorensen, S., Zicchino, L., 2005. Stress tests of uk banks using a var approach. Bank of England Working Paper Series No. 282. doi:10.2139/ssrn.872693.

Horváth, B.L., Huizinga, H., 2015. Does the european financial stability facility bail out sovereigns or banks? an event study. Journal of Money, Credit and Banking 47, 177–206. doi:10.1111/jmcb.12173.

Houweling, P., Vorst, T., 2005. Pricing default swaps: Empirical evidence. Journal of International Money and Finance 24, 1200–1225. doi:10.1016/j.jimonfin.2005.08.009.

Hsu, D.A., 1984. The behavior of stock returns: Is it stationary of evolutionary? Journal of Financial and Quantitative Analysis 19, 11–28. doi:10.2307/2330998.

International Swaps and Derivatives Association, 2023. Single-name cds market update. URL: https://www.isda.org/a/0jLgE/Single-name-CDS-Market-Update.pdf.

James, C., 1983. An analysis of intra-industry differences in the effect of regulation. Journal of Monetary Economics 12, 417–432. doi:10.1016/0304-3932(83)90062-4.

Jarociński, M., Karadi, P., 2020. Deconstructing monetary policy surprises— the role of information shocks. American Economic Journal: Macroeconomics 12, 1–43. doi:10.1257/mac.20180090.

Jensen, G.R., Mercer, J.M., Johnson, R.R., 1996. Business conditions, monetary policy, and expected security returns. Journal of Financial Economics 40, 213–237. doi:10.1016/0304-405X(96)89537-7.

Jensen, M.C., 1986. Agency costs of free cash flow, corporate finance, and takeovers. The American Economic Review 76, 323–329. URL: https://www.jstor.org/stable/1818789.

Jensen, T.K., Johnson, R.R., McNamara, M.J., 2019. Funding conditions and insurance stock returns: Do insurance stocks really benefit from rising interest rate regimes? Risk Management and Insurance Review 22, 367–391. doi:10.1111/rmir.12133.

Kakinaka, S., Umeno, K., 2020. Characterizing cryptocurrency market with lévy's stable distributions. Journal of the Physical Society of Japan 89, 024802. doi:10.7566/JPSJ.89.024802.

Kashyap, A., Stein, J., 1995. The impact of monetary policy on bank balance sheets. Carnegie-Rochester Conference Series on Public Policy 42, 151–195. doi:10.1016/0167-2231(95)00032-U.

Kashyap, A., Stein, J., 2000. What do a million observations on banks say about the transmission of monetary policy? American Economic Review 90, 407–428. doi:10.1257/aer.90.3.407.

Kaufmann, C., Leyva, J., Storz, M., 2024. Insurance corporations' balance sheets, financial stability and monetary policy. ECB Working Paper Series No. 2892. URL: https://www.ecb.europa.eu/pub/pdf/scpwps/ecb.wp2892~8f94a17da7.en.pdf.

Keeley, M.C., 1990. Deposit insurance, risk, and market power in banking. The American Economic Review 80, 1183–1200. URL: https://www.jstor.org/stable/2006769.

Killins, R.N., Chen, H., 2022. The impact of the yield curve on the equity returns of insurance companies. International Journal of Finance & Economics 27, 1134–1153. doi:10.1002/ijfe.2205.

Kim, S.J., Lee, L., Wu, E., 2013. The impact of domestic and international monetary policy news on u.s. and german bank stocks, in: Jeon, B.N., Olivero, M.P. (Eds.), Global Banking, Financial Markets and Crises. Emerald Group Publishing Limited. volume 14 of *International Finance Review*, pp. 175–210. doi:10.1108/S1569-3767(2013)0000014010.

Koch, J.A., Islam, M.S., 2024. Impact of higher federal funds rates on bank risk during higher inflation in the u.s. Finance Research Letters 60, 104866. doi:10.1016/j.frl.2023.104866.

Koch, T.W., MacDonald, S.S., 2015. Bank management. 8. ed., Cengage Learning, Boston, MA. URL: https://permalink.obvsg.at/AC12135820.

Kolari, J.W., Pynnönen, S., 2010. Event study testing with cross-sectional correlation of abnormal returns. Review of Financial Studies 23, 3996–4025. doi:10.1093/rfs/hhq072.

Koont, N., Santos, T., Zingales, L., 2024. Destabilizing digital "bank walks". National Bureau of Economic Research Working Paper No. 32601. doi:10.3386/w32601.

Kubitza, C., 2023. Investor-driven corporate finance: evidence from insurance markets. ECB Working Paper Series No. 2816. URL: https://www.ecb.europa.eu/pub/pdf/scpwps/ecb.wp2816~eeeafe78aa.en.pdf.

Kuo Chuen, D.L., Guo, L., Wang, Y., 2017. Cryptocurrency: A new investment opportunity? The Journal of Alternative Investments 20, 16–40. doi:10.3905/jai.2018.20.3.016.

Kuttner, K.N., 2001. Monetary policy surprises and interest rates: Evidence from the fed funds futures market. Journal of Monetary Economics 47, 523–544. doi:10.1016/S0304-3932(01)00055-1.

Laeven, L., Ratnovski, L., Tong, H., 2016. Bank size, capital, and systemic risk: Some international evidence. Journal of Banking & Finance 69, S25–S34. doi:10.1016/j.jbankfin.2015.06.022.

Laeven, L., Tong, H., 2012. Us monetary shocks and global stock prices. Journal of Financial Intermediation 21, 530–547. doi:10.1016/j.jfi.2012.02.002.

Lamdin, D.J., 2001. Implementing and interpreting event studies of regulatory changes. Journal of Economics and Business 53, 171–183. doi:10.1016/S0148-6195(01)00035-2.

Lintner, J., 1965. The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. The Review of Economics and Statistics 47, 13–37. doi:10.2307/1924119.

Liu, X., Zhu, X.H., Qiu, P., Chen, W., 2012. A correlation-matrix-based hierarchical clustering method for functional connectivity analysis. Journal of Neuroscience Methods 211, 94–102. doi:10.1016/j.jneumeth.2012.08.016.

Liu, Y., Tsyvinski, A., 2021. Risks and returns of cryptocurrency. Review of Financial Studies 34, 2689–2727. doi:10.1093/rfs/hhaa113.

Lobo, B.J., 2000. Asymmetric effects of interest rate changes on stock prices. The Financial Review 35, 125–144. doi:10.1111/j.1540-6288.2000.tb01424.x.

Longstaff, F.A., Mithal, S., Neis, E., 2005. Corporate yield spreads: Default risk or liquidity? new evidence from the credit default swap market. The Journal of Finance 60, 2213–2253. doi:10.1111/j.1540-6261.2005.00797.x.

Lu, C., Shen, Y., So, R.W., 1999. Wealth effects of the basle accord on small banks. Journal of Economics and Finance 23, 246–254. doi:10.1007/BF02757709.

MacKinlay, A.C., 1997. Event studies in economics and finance. Journal of Economic Literature 35, 13–39. URL: https://www.jstor.org/stable/2729691.

Majoros, S., Zempléni, A., 2018. Multivariate stable distributions and their applications for modelling cryptocurrency-returns. Working Paper. URL: http://arxiv.org/pdf/1810.09521v1.

Mamun, A.A., Hassan, M.K., van Lai, S., 2004. The impact of the gramm-leach-bliley act on the financial services industry. Journal of Economics and Finance 28, 333–347. doi:10.1007/BF02751736.

Männasoo, K., Mayes, D.G., 2009. Explaining bank distress in eastern european transition economies. Journal of Banking & Finance 33, 244–253. doi:10.1016/j.jbankfin.2008.07.016.

Markowitz, H.M., 1952. Portfolio selection. The Journal of Finance 7, 77–91. doi:10.2307/2975974.

Mentz, M., Schiereck, D., 2008. Cross-border mergers and the cross-border effect: the case of the automotive supply industry. Review of Managerial Science 2, 199–218. doi:10.1007/s11846-008-0022-1.

Methling, F., von Nitzsch, R., 2019. Thematic portfolio optimization: challenging the core satellite approach. Financial Markets and Portfolio Management 33, 133–154. doi:10.1007/s11408-019-00329-0.

Mikkelson, W.H., Partch, M.M., 1988. Withdrawn security offerings. Journal of Financial and Quantitative Analysis 23, 119–133. doi:10.2307/2330876.

Miles, D., Yang, J., Marcheggiano, G., 2013. Optimal bank capital. The Economic Journal 123, 1–37. doi:10.1111/j.1468-0297.2012.02521.x.

Miranda-Agrippino, S., Ricco, G., 2021. The transmission of monetary policy shocks. American Economic Journal: Macroeconomics 13, 74–107. doi:10.1257/mac.20180124.

Moenninghoff, S.C., Ongena, S., Wieandt, A., 2015. The perennial challenge to counter too-big-to-fail in banking: Empirical evidence from the new international regulation dealing with global systemically important banks. Journal of Banking & Finance 61, 221–236. doi:10.1016/j.jbankfin.2015.01.017.

Möhlmann, A., 2021. Interest rate risk of life insurers: Evidence from accounting data. Financial Management 50, 587–612. doi:10.1111/fima.12305.

Mojon, B., 2000. Financial structure and the interest rate channel of ecb monetary policy. ECB Working Paper Series No. 40. URL: https://www.ecb.europa.eu/pub/pdf/scpwps/ecbwp040.pdf.

Morse, D., 1984. An econometric analysis of the choice of daily versus monthly returns in tests of information content. Journal of Accounting Research 22, 605–623. doi:10.2307/2490667.

Mossin, J., 1966. Equilibrium in a capital asset market. Econometrica 34, 768–783. doi:10.2307/1910098.

Myers, S.C., Majluf, N.S., 1984. Corporate financing and investment decisions when firms have information that investors do not have. Journal of Financial Economics 13, 187–221. doi:10.1016/0304-405X(84)90023-0.

Myers, S.C., Rajan, R.G., 1998. The paradox of liquidity. The Quarterly Journal of Economics 113, 733–771. doi:10.1162/003355398555739.

Nakamoto, S., 2008. Bitcoin: A peer-to-peer electronic cash system. URL: https://bitcoin.org/bitcoin.pdf.

Needham, D., 1983. The economics and politics of regulation: A behavioral approach. Little Brown and Co, Boston.

Nilsen, J.H., 2002. Trade credit and the bank lending channel. Journal of Money, Credit and Banking 34, 226–253. URL: https://www.jstor.org/stable/3270684.

Nolan, J.P., 2020. Univariate Stable Distributions: Models for Heavy Tailed Data. Springer Series in Operations Research and Financial Engineering. 1st ed. 2020 ed., Springer International Publishing and Imprint: Springer, Cham. doi:10.1007/978-3-030-52915-4.

Office of the Comptroller of the Currency, Department of the Treasury, Board of Governors of the Federal Reserve System, Federal Deposit Insurance Corporation, 2014. Liquidity coverage ratio: Liquidity risk measurement standards. URL: https://www.federalregister.gov/documents/2014/10/10/2014-22520/liquidity-coverage-ratio-liquidity-risk-measurement-standards.

Office of the Comptroller of the Currency, Department of the Treasury, Board of Governors of the Federal Reserve System, Federal Deposit Insurance Corporation, 2016. Net stable funding ratio: Liquidity risk measurement standards and disclosure requirements. URL: https://www.federalregister.gov/documents/2016/06/01/2016-11505/net-stable-funding-ratio-liquidity-risk-measurement-standards-and-disclosure-requirements.

Office of the Comptroller of the Currency, Department of the Treasury, Board of Governors of the Federal Reserve System, Federal Deposit Insurance Corporation, 2021. Net stable funding ratio: Liquidity risk measurement standards and disclosure requirements. URL: https://www.federalregister.gov/documents/2021/02/11/2020-26546/net-stable-funding-ratio-liquidity-risk-measurement-standards-and-disclosure-requirements.

Office of the Comptroller of the Currency, Treasury, Board of Governors of the Federal Reserve System, 2013. Regulatory capital rules: Regulatory capital, implementation of basel iii, capital adequacy, transition provisions, prompt corrective action, standardized approach for risk-weighted assets, market discipline and disclosure requirements, advanced approaches risk-based capital rule, and market risk capital rule. URL: https://www.federalregister.gov/documents/2013/10/11/2013-21653/regulatory-capital-rules-regulatory-capital-implementation-of-basel-iii-capital-adequacy-transition.

Office of the Comptroller of the Currency, Treasury, Board of Governors of the Federal Reserve System, Federal Deposit Insurance Corporation, 2019. Changes to applicability thresholds for regulatory capital and liquidity requirements. URL: https://www.federalregister.gov/documents/2019/11/01/2019-23800/changes-to-applicability-thresholds-for-regulatory-capital-and-liquidity-requirements.

Office of the Comptroller of the Currency, Treasury, Board of Governors of the Federal Reserve System, Federal Deposit Insurance Corporation, 2023. Regulatory capital rule: Large banking organizations and banking organizations with significant trading activity. URL: https://www.federalregister.gov/documents/2023/09/18/2023-19200/regulatory-capital-rule-large-banking-organizations-and-banking-organizations-with-significant.

Ongena, S., Smith, D.C., Michalsen, D., 2003. Firms and their distressed banks: lessons from the norwegian banking crisis. Journal of Financial Economics 67, 81–112. doi:10.1016/S0304-405X(02)00232-5.

Osterrieder, J., Strika, M., Lorenz, J., 2017. Bitcoin and cryptocurrencies—not for the faint-hearted. International Finance and Banking 4, 56–94. doi:10.5296/ifb.v4i1.10451.

Paddrik, M.E., Tompaidis, S., 2019. Market-making costs and liquidity: Evidence from cds markets. SSRN Electronic Journal. doi:10.2139/ssrn.3351288.

Pancotto, L., ap Gwilym, O., Williams, J., 2020. Market reactions to the implementation of the banking union in europe. The European Journal of Finance 26, 640–665. doi:10.1080/1351847X.2019.1661264.

Poggio, T., Girosi, F., 1990. Regularization algorithms for learning that are equivalent to multilayer networks. Science (New York, N.Y.) 247, 978–982. doi:10.1126/science.247.4945.978.

Polasik, M., Piotrowska, A.I., Wisniewski, T.P., Kotkowski, R., Lightfoot, G., 2015. Price fluctuations and the use of bitcoin: An empirical inquiry. International Journal of Electronic Commerce 20, 9–49. doi:10.1080/10864415.2016.1061413.

Powell, M.J.D., 1977. Restart procedures for the conjugate gradient method. Mathematical Programming 12, 241–254. doi:10.1007/bf01593790.

Ratnovski, L., 2009. Bank liquidity regulation and the lender of last resort. Journal of Financial Intermediation 18, 541–558. doi:10.1016/j.jfi.2007.08.001.

Ricci, O., 2015. The impact of monetary policy announcements on the stock price of large european banks during the financial crisis. Journal of Banking & Finance 52, 245–255. doi:10.1016/j.jbankfin.2014.07.001.

Rigobon, R., Sack, B., 2004. The impact of monetary policy on asset prices. Journal of Monetary Economics 51, 1553–1575. doi:10.1016/j.jmoneco.2004.02.004.

Rivin, I., Scevola, C., Davis, R., 2017. Cci30® - the crypto currencies index. URL: https://cci30.com/.

Ross, S.A., 1976. The arbitrage theory of capital asset pricing. Journal of Economic Theory 13, 341–360. doi:10.1016/0022-0531(76)90046-6.

Sahin, F., 1997. A Radial Basis Function Approach to a Color Image Classification Problem in a Real Time Industrial Application: Thesis. Virgina Tech, Blacksburg, Virginia. URL: http://hdl.handle.net/10919/36847.

Sakoe, H., Chiba, S., 1978. Dynamic programming algorithm optimization for spoken word recognition. IEEE Transactions on Acoustics, Speech, and Signal Processing 26, 43–49. doi:10.1109/TASSP.1978.1163055.

Samuelson, P.A., 1945. The effect of interest rate increases on the banking system. The American Economic Review 35, 16–27. URL: https://www.jstor.org/stable/1810106.

Sarin, N., Summers, L.H., 2016. Understanding bank risk through market measures. Brookings Papers on Economic Activity Fall 2016, 57–109. URL: http://www.jstor.org/stable/90000432.

Schäfer, A., Schnabel, I., Di Weder Mauro, B., 2016. Financial sector reform after the subprime crisis: Has anything happened? Review of Finance 20, 77–125. doi:10.1093/rof/rfu055.

Schmitz, T., Hoffmann, I., 2020. Re-evaluating cryptocurrencies' contribution to portfolio diversification – a portfolio analysis with special focus on german investors. SSRN Electronic Journal. doi:10.2139/ssrn.3625458.

Sharpe, W.F., 1963. A simplified model for portfolio analysis. Management Science 9, 277–293. doi:10.1287/mnsc.9.2.277.

Sharpe, W.F., 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. The Journal of Finance 19, 425–442. doi:10.1111/j.1540-6261.1964.tb02865.x.

Sigaki, H.Y.D., Perc, M., Ribeiro, H.V., 2019. Clustering patterns in efficiency and the coming-of-age of the cryptocurrency market. Scientific reports 9, 1440. doi:10.1038/s41598-018-37773-3.

Simion, G., Rigoni, U., Cavezzali, E., Veller, A., 2024. Basel liquidity regulation and credit risk market perception: Evidence from large european banks. Research in International Business and Finance 69, 102228. doi:10.1016/j.ribaf.2024.102228.

Slovin, M.B., Sushka, M.E., Bendeck, Y.M., 1990. The market valuation effects of reserve regulation. Journal of Monetary Economics 25, 3–19. doi:10.1016/0304-3932(90)90041-2.

Sondermann, D., Bohl, M.T., Siklos, P.L., 2009. The euro area stock market channel: Does one size fit all? Finance Research Letters 6, 230–235. doi:10.1016/j.frl.2009.08.001.

Stigler, G.J., 1971. The theory of economic regulation. The Bell Journal of Economics and Management Science 2, 3–31. doi:10.2307/3003160.

Stiglitz, J.E., Weiss, A., 1981. Credit rationing in markets with imperfect information. The American Economic Review 71, 393–410. URL: https://www.jstor.org/stable/1802787.

Strong, N., 1992. Modelling abnormal returns: A review article. Journal of Business Finance & Accounting 19, 533–553. doi:10.1111/j.1468-5957.1992.tb00643.x.

Sundaresan, S., Xiao, K., 2024. Liquidity regulation and banks: Theory and evidence. Journal of Financial Economics 151, 103747. doi:10.1016/j.jfineco.2023.103747.

Swanson, E.T., 2021. Measuring the effects of federal reserve forward guidance and asset purchases on financial markets. Journal of Monetary Economics 118, 32–53. doi:10.1016/j.jmoneco.2020.09.003.

Theil, H., 1971. Principles of econometrics. John Wiley & Sons, New York.

Thorbecke, W., 1997. On stock market returns and monetary policy. The Journal of Finance 52, 635–654. doi:10.2307/2329493.

Thornton, D.L., 1998. Tests of the market's reaction to federal funds rate target changes. Federal Reserve Bank of St. Louis Review, 25–36 .

Tikhonov, A.N., 1943. [translated:] on the stability of inverse problems. Doklady Akademii Nauk SSSR 39, 195–198.

Tikhonov, A.N., 1963. [translated:] solution of incorrectly formulated problems and the regularization method. Doklady Akademii Nauk SSSR , 501–504.

Trimborn, S., Härdle, W.K., 2018. Crix an index for cryptocurrencies. Journal of Empirical Finance 49, 107–122. doi:10.1016/j.jempfin.2018.08.004.

Trimborn, S., Li, M., Härdle, W.K., 2020. Investing with cryptocurrencies—a liquidity constrained investment approach. Journal of Financial Econometrics 18, 280–306. doi:10.1093/jjfinec/nbz016.

Wagster, J.D., 1996. Impact of the 1988 basle accord on international banks. The Journal of Finance 51, 1321–1346. doi:10.2307/2329396.

Wongswan, J., 2009. The response of global equity indexes to u.s. monetary policy announcements. Journal of International Money and Finance 28, 344–365. doi:10.1016/j.jimonfin.2008.03.003.

Yermack, D., 2024. Is bitcoin a real currency? an economic appraisal, in: Handbook of Digital Currency. Elsevier, pp. 29–40. doi:10.1016/B978-0-323-98973-2.00014-9.

Yildirim, H.S., Kwag, S.W., Collins, M.C., 2006. An examination of the equity market response to the gramm-leach-bliley act across commercial banking, investment banking, and insurance firms. Journal of Business Finance & Accounting 33, 1629–1649. doi:10.1111/j.1468-5957.2006.00642.x.

Yin, H., Yang, J., 2013. Bank characteristics and stock reactions to federal funds rate target changes. Applied Financial Economics 23, 1755–1764. doi:10.1080/09603107.2013.851770.

Yin, H., Yang, J., Handorf, W.C., 2010. State dependency of bank stock reaction to federal fund rate target changes. Journal of Financial Research 33, 289–315. doi:10.1111/j.1475-6803.2010.01272.x.

Appendices

A Event Description

Table A.21: Market Events and Predicted Impact on Regulation

Event	Type and Name	Impact	Short Description
1 October 12, 2007	**Consultative**: Guidelines for Computing Capital for Incremental Default Risk in the Trading Book	Tightened	Stricter guidelines for calculating incremental default risk charge (IDRC) for trading book positions.
2 July 22, 2008	**Press release**: Computing Capital for Incremental Risk in the Trading Book **Consultative**: Guidelines for Computing Capital for Incremental Risk in the Trading Book[59] **Consultative**: Proposed revisions to the Basel II market risk framework	Tightened	IDRC is to be replaced by IRC, which takes into account not only default risk of credit-dependent instruments in the trading book but also losses due to changes in credit ratings, credit spreads and liquidity. The capital requirements for these instruments in particular is to be increased in order to prevent regulatory arbitrage between the banking and the trading book.
3 January 16, 2009	**Consultative**: Guidelines for computing capital for incremental risk in the trading book **Consultative**: Revisions to the Basel II market risk framework	Tightened	IRC includes default risk and migration risk and has to be calculated for unsecuritized credit products. For securitized instruments, the capital requirements of the banking book have to be applied. The capital framework of the trading book is supplemented by a VaR based on a one-year historical stress period. This at least doubles regulatory capital. Furthermore, the BCBS proposes to remove the 4% preferential treatment of specific risks of liquid and diversified equity portfolios so that 8% would be required.
4 July 13, 2009	**Standards**: Guidelines for computing capital for incremental risk in the trading book **Standards**: Revisions to the Basel II market risk framework	Tightened	Rules are adopted as standards without significant changes. Although the capital requirements of the banking book apply to securitized products, banks may calculate a comprehensive risk measure (CRM) for so-called correlation trading activities with the permission of the supervisory authority. This framework would replace the IRC and specific risk charge for those portfolios, but it would be subject to strict requirements, stress tests and a floor given by the banking book capital requirement.
5 June 18, 2010	**Press release**: Adjustments to the Basel II market risk framework announced by the Basel Committee	Weakened	BCBS grants nine-month extension to implement rules adopted in July 2009. Furthermore, net long and short positions of non-correlation trading securitization positions can be offset during the subsequent two-year transition period after the implementation of the market risk framework on December 31, 2011. The floor for the correlation trading securitization positions is set to 8% of the standard method.

[59] The BCBS information concerning the publication date differs between July 22, 2008 and July 23, 2008. July 22, 2008 is defined as event day with the corresponding press release.

6 May 3, 2012	**Consultative**: The fundamental review of the trading book	Tightened	BCBS proposes a more strict boundary between the banking and the trading book to reduce regulatory arbitrage. VaR models shall be replaced by expected shortfall models that incorporate tail risk. A revised standard approach should be constructed that is risk sensitive and a credible fallback for internal models. The calculation of the standard approach should be mandatory if it is necessary as a floor or surcharge for internal models. In the internal model, the possibility of taking diversification into account is to be reduced, with hedging and diversification being more closely aligned in both approaches. Consistent with the stressed VaR approach from Basel II.5, a revised framework in both the internal models-based and the standardized approach should be calibrated on a period of significant financial stress.
7 Otober 31, 2013	**Consultative**: Fundamental review of the trading book: A revised market risk framework	Tightened	The points raised in the first consultation paper have now been elaborated in more detail and incorporated into a draft text for the new market risk framework.
8 December 19, 2014	**Consultative**: Fundamental review of the trading book: outstanding issues	Weakened	Development for a treatment of internal risk transfers from the banking to the trading book. There are simplifications for the standard approach, which, in addition to the cash-flow-based approach, also includes a sensitivity-based. Furthermore, revisions to the internal models approach with varying liquidity horizons facilitate implementation, which is easier for banks to implement due to internal systems.
9 June 8, 2015	**Consultative**: Interest rate risk in the banking book	Tightened	BCBS proposes two potential options for dealing with interest rate risk in the banking book to ensure that banks have enough capital to address losses due to an interest rate increase, especially in times of very low interest rates. The first option involves a minimum Pillar 1 capital requirement, whereas the second proposal involves a quantitative disclosure against the background of Pillar 2.
10 January 14, 2016	**Standards**: Minimum capital requirements for the trading book	Weakened	New market risk framework comes into force on January 1, 2019.
11 April 21, 2016	**Standards**: Interest rate risk in the banking book	Weakened	BCBS decides against capital requirements for interest rate risk in the banking book. Only disclosure requirements and management guidelines will be tightened.
12 June 29, 2017	**Consultative**: Simplified alternative to the standardized approach to market risk capital requirements	Weakened	BCBS proposes a simplified standardized approach for smaller banks that significantly lowers operational hurdles. Furthermore, under this approach, vega and curvature risk do not have to be backed by capital. The calculation is simplified and comes with reduced risk factor granularity correlation scenarios. As an alternative, the BCBS proposes to use a modified version of the Basel II.5 standardized approach.
13 December 7, 2017	**Press release**: Governors and Heads of Supervision finalize Basel III reforms	Weakened	Implementation of the market risk framework is postponed by three years to January 1, 2022.

14 March 22, 2018	**Consultative**: Revisions to the minimum capital requirements for market risk	Weakened	BCBS proposes refinements to the standardized approach, including less conservative consideration of liquid foreign exchange (FX) pairs and correlation scenarios and changes to non-linear instruments. Furthermore, BCBS proposes to reduce the risk weights for the general interest rate risk class by 20-40%, and equity and FX risk classes by 25-50%. As an alternative to the standardized approach for small banks, the Basel II.5 standardized approach with a more conservative calibration is proposed.
15 January 14, 2019	**Standard**: Minimum capital requirements for market risk	Tightened	The market risk framework was adopted without significant changes. Compared to Basel II.5, a weighted average increase of 22% in market risk capital is estimated.

This table provides information on 15 announcements regarding market risk regulation by the BCBS. It includes an assessment of whether each announcement will tighten or weaken regulation, along with a brief description.

Table A.22: Credit Events and Predicted Impact on Regulation

Event	Type and Name	Impact	Short Description
1 November 17, 2008	**Press release:** Nout Wellink: The Importance of Banking Supervision in Financial Stability	Tightened	The BCBS proposes to increase regulatory capital for credit risk and the quality of Tier 1. A capital buffer is proposed that banks need to build up in "good times" and that can be drawn in periods of stress.
2 January 16, 2009	**Consultative:** Proposed enhancements to the Basel II framework	Tightened	The BCBS proposes higher capital requirements for resecuritizations in the banking book.
3 July 13, 2009	**Standards:** Enhancements to the Basel II framework	Tightened	Higher risk weights for resecuritizations are suggested. These regulations are supplemented by stricter risk management and stronger disclosure requirements.
4 September 7, 2009	**Press release:** Comprehensive response to the global banking crisis	Tightened	The Group of Central Bank Governors and Heads of Supervision reach agreement. The introduction of a framework for countercyclical capital buffers is planned. Tier 1 capital shall include predominantly common shares and retained earnings.
5 December 17, 2009	**Consultative:** Strengthening the resilience of the banking sector	Tightened	Tier 1 capital predominantly includes common equity and retained earnings, which could hit EU banks that use hybrid capital particularly hard, since hybrid capital will be phased out completely. Furthermore, the BCBS proposes to strengthen capital requirements for counterparty credit risk exposures resulting from derivatives, repos and securities financing transactions. A capital conservation buffer shall force banks to build up Tier 1 capital that can be drawn in periods of stress. The countercyclical capital buffer shall dampen procyclicality and will likely be implemented at the jurisdiction level, if necessary.
6 July 16, 2010	**Consultative:** Countercyclical capital buffer proposal	Tightened	In normal times, the buffer is set at zero. If the national regulator detects signs of a credit bubble, it can force banks to comply with the buffer within twelve months. Tier 1 capital must be used.

7 July 26, 2010	**Press release**: The Group of Governors and Heads of Supervision reach broad agreement on Basel Committee capital and liquidity reform package	Weakened	An annex to the press release is published. Minority stakes in bank subsidiaries qualify as regulatory capital. Banks are allowed to include holdings in unconsolidated financial institutions, mortgage servicing rights and deferred tax assets up to 10% of the common equity component of tier one capital.
8 September 13, 2010	**Press release:** Group of Governors and Heads of Supervision announces higher global minimum capital standards[60]	Weakened	The capital adequacy rules will not be introduced until 2013, and there is with a generous transition period until 2019. The capital conservation buffer will be phased in only from 2016. Furthermore, it is unclear when and how the countercyclical capital buffer will be introduced. Capital instruments that no longer qualify as regulatory capital are phased out over ten years starting in 2013.
9 December 16, 2010	**Standards:** Basel III: A global regulatory framework for more resilient banks and banking systems	Tightened	Proposed rules are adopted as standards without significant changes. Countercyclical capital buffer is to be met with Common Equity Tier 1 and set between 0 and 2.5% by national authorities, depending on excessive credit growth. It is phased in with the capital conservation buffer.
10 November 2, 2011	**Consultative:** Capitalisation of bank exposures to central counterparties[61]	Tightened	There is only relief for smaller banks that clear through larger banks. The BCBS does not change the original proposal for a two percent risk weighting of exposures to central counterparties, which, according to the banks, counteracts the BCBS' desire for central clearing.
11 July 6, 2012	**Consultative:** Margin requirements for non-centrally-cleared derivatives	Tightened	Issued draft proposes margin requirements and a framework for non-centrally derivatives to promote the use of central counterparties.
12 July 25, 2012	**Standards:** Capital requirements for bank exposures to central counterparties	Tightened	The former proposal is reaffirmed as standard. Furthermore, banks can choose between a simplified and a risk sensitive approach to determine their capital required for exposures to default funds.
13 December 18, 2012	**Consultative:** Revisions to the Basel Securitization Framework	Tightened	After resecuritizations were already given a higher risk weight in the standard of July 13, 2009, the securitization framework is now being completely revised. The risk weight floor for internal models will initially be raised from 7% to 20%. Both internal and standard approaches are to be revised so that they are more closely aligned. Furthermore, reliance on external ratings is to be reduced.
14 February 15, 2013	**Consultative:** Margin requirements for non-centrally cleared derivatives	Weakened	The initial draft is eased, since a universal initial margin threshold of €50 million is now proposed. Furthermore, after a transition phase (depending on the notional amount of non-centrally cleared derivatives), the rules do not have to be applied by everyone until 2019. Contrary to the previous proposal, the BCBS is seeking market participants' advice on whether financial firms should be permitted to reuse collateral that has been used as margin.
15 June 28, 2013	**Consultative:** Capital requirements for bank exposures to central counterparties	Tightened	The BCBS argues that an interim standard was implemented and that it needs an overhaul.

[60] The publication is dated Sunday, September 12, 2010 and the next trading day is set as the event day.

[61] An initial consultation paper dated December 20, 2010 is excluded because its event window would overlap with the event window of event 9.

16 September 2, 2013	**Standards:** Margin requirements for non-centrally cleared derivatives	Weakened	The standard introduced excludes foreign exchange derivatives from initial margin requirements.Furthermore, subject to strict requirements, a unique re-hypothecation of initial margin collateral is permitted
17 December 19, 2013	**Consultative:** Revisions to the securitization framework	Weakened	The hierarchy of the securitization framework is designed similar to that of the credit risk one and therefore simplified to the initial proposal, which results in substantial reductions in capital. The risk-weight floor for the internal ratings based approach is set to 15%, instead of 20% from the previous proposal.
18 April 10, 2014	**Standards:** Capital requirements for bank exposures to central counterparties - final standard	Tightened	There is a new approach to determining capital requirements for bank exposures to qualifying central counterparties as well as a limit on the capital requirement compared to non-qualifying central counterparties. The standard will become mandatory as of January 01, 2017.
19 December 11, 2014	**Standards:** Revisions to the securitization framework	Tightened	The prior proposal is finalized as standard without significant changes. The securitization framework will be implemented in January 2018.
20 December 22, 2014	**Consultative:** Revisions to the standardized approach for credit risk	Tightened	The draft proposes to reduce banks' reliance on external ratings and thus to tighten their own risk management with respect to the standardized approach for credit risk.
21 March 18, 2015	**Standards:** Margin requirements for non-centrally cleared derivatives	Weakened	The beginning of the four-year phase-in period is postponed from December 1, 2015 to September 1, 2016.
22 December 10, 2015	**Consultative:** Revisions to the Standardized Approach for credit risk	Weakened	The complete ban on the use of external ratings is rescinded. They can still be used for exposures to companies and banks, although the mechanistic nature shall be mitigated.
23 March 24, 2016	**Consultative:** Reducing variation in credit risk-weighted assets - constraints on the use of internal model approaches	Tightened	The use of the advanced and foundation IRBA is to be prohibited for credit exposures to banks, other financial companies as well as large companies (total assets > €50 billion) and equities. Furthermore, a minimum input floor for the IRBA parameters is given. The BCBS proposes an output floor of the IRB approaches calibrated in the range of 60% to 90% in relation to the standardized approach.
24 July 11, 2016	**Standards:** Revisions to the securitization framework	Weakened	Compared to the November 2015 consultation paper, the risk weights of simple, transparent and comparable (STC) securitisations are lowered and the risk floor for senior exposures has been reduced from 15% to 10%.
25 December 7, 2017	**Standards:** Basel III: Finalising post-crisis reforms	Weakened	Contrary to the previous consultative document, the foundation IRBA may be used for exposures to banks, large and medium-sized enterprises and other financial companies. The previously discussed capital output floor for the IRB approaches lied in the range of 60% to 90% and is now set to the higher of IRBA RWA or 72.5% of the RWA under the standardized approach. A transitional agreement for the output floor is agreed so that it is obligatory on January 1, 2027. The risk weights under the standardized approach have also been weakened compared with the consultation paper. The revised standardized and the IRB approaches will not be implemented before January 1, 2022.

26 July 23, 2019	**Standards:** Margin requirements for non-centrally cleared derivatives	Weakened	The last implementation phase for institutions with the lowest threshold (notional derivative amount of more than €8 billion) is delayed by one year.

This table provides information on 26 announcements regarding credit risk regulation by the BCBS. It includes an assessment of whether each announcement will tighten or weaken regulation, along with a brief description.

Table A.23: Liquidity Events and Predicted Impact on Regulation

Event	Type and Name	Impact	Short Description
1 February 21, 2008	**Sound practices**: Liquidity Risk: Management and Supervisory Challenges	Tightened	Summary of the main findings of a BCBS working group on liquidity risk, assessing how banks address and manage it; these findings also take into account the GFC.
2 June 17, 2008	**Consultative**: Principles for Sound Liquidity Risk Management and Supervision	Tightened	BCBS proposes stronger liquidity risk management framework for banks and enhanced supervisory oversight. This consultative paper is a substantial revision of guidelines from 2000.
3 September 25, 2008	**Guidelines**: Principles for Sound Liquidity Risk Management and Supervision	Tightened	The final version of the previous consultation paper is published without significant changes.
4 December 17, 2009	**Consultative**: International framework for liquidity risk measurement, standards and monitoring	Tightened	The BCBS proposes two new liquidity metrics, the LCR and the NSFR. While the former metric aims to ensure that banks have sufficient high quality liquid assets (HQLA) over a 30-day period under stress, the goal of the NSFR is to ensure stable funding of long-term and illiquid assets over a one-year period.
5 July 26, 2010	**Press release**: The Group of Governors and Heads of Supervision reach broad agreement on Basel Committee capital and liquidity reform package	Weakened	An annex to the press release is published and both liquidity metrics are alleviated. For the LCR, run-off factors of retail and small and medium-sized enterprise (SME) deposits are reduced. The definition of HQLA is relaxed, which now also qualifies certain high-quality corporate bonds, for example. Retail and SME deposits receive a higher available stable funding (ASF) factor, with the required stable funding (RSF) factor for residential mortgages being reduced. Furthermore, the BCBS announces that some refinements to both metrics might be possible.
6 December 16, 2010	**Standards**: Basel III: International framework for liquidity risk measurement, standards and monitoring	Tightened	The BCBS publishes the Basel III rules text and results of a quantitative impact study (QIS). Furthermore, the final standards for liquidity management are published, no significant changes have been made compared to the annex of July 26, 2010.
7 January 07, 2013	**Standards**: Basel III: The Liquidity Coverage Ratio and liquidity risk monitoring tools	Weakened	Final standard of the LCR is issued by the BCBS, with the metric being phased in from January 1, 2015 (60%) until January 1, 2019 (100%). The scope of assets that can be used as HQLA is expanded. Furthermore, some inflow and outflow rates are recalibrated (see Annex 2 *Complete set of agreed changes to the formulation of the Liquidity Coverage Ratio published in December 2010* for concrete changes).
8 July 19, 2013	**Consultative**: Liquidity coverage ratio disclosure standards	Tightened	The BCBS proposes disclosure requirements for the LCR.

9 January 13, 2014[62]	**Standards**: Liquidity coverage ratio disclosure standards **Consultative**: Basel III: the Net stable funding ratio	Weakened	The BCBS issues the standard for the LCR disclosure requirements. In the second document, the BCBS relaxes the NSFR with respect to a broader recognition and higher ASF factor for deposits while increasing consistency with the LCR. In addition, cliff effects in the measurement of ASF and RSF shall be mitigated.
10 October 31, 2014	**Standards**: Basel III: the net stable funding ratio	Tightened	The standard of the NSFR is finalized. BCBS makes only minor changes to the RSF. The standard will be implemented as of January 01, 2018.
11 December 9, 2014	**Consultative**: Net stable funding ratio disclosure standards	Tightened	For reasons of market discipline and transparency, the BCBS proposes that banks need to disclose their NSFR according to a given template.
12 June 22, 2015	**Standards**: Net stable funding ratio disclosure standards	Tightened	The BCBS is introducing the disclosure requirements for the NSFR as a standard in parallel with the introduction of the BCBS on January 01, 2018.
13 October 6, 2017	**Standards**: Implementation of net stable funding ratio and treatment of derivative liabilities	Weakened	The BCBS allows countries to lower the RSF factor for derivative liabilities from 20% to as low as 5%. In this respect, countries have discretion in setting a floor, which should simplify the implementation of the NSFR as of January 01, 2018.

This table provides information on 13 announcements regarding liquidity risk regulation by the BCBS. It includes an assessment of whether each announcement will tighten or weaken regulation, along with a brief description.

[62]The event date is set to January 13, 2014, because both announcements are made on Sunday January 12, 2014.

B Keywords for Media Analysis

Table B.24: Keywords for Evaluating International Media Coverage

Market Risk	Credit Risk	Liquidity Risk
bank regulation	bank regulation	bank regulation
BIS	BIS	BIS
Bank for International Settlements	Bank for International Settlements	Bank for International Settlements
BCBS	BCBS	BCBS
Basel Committee	Basel Committee	Basel Committee
Basel Committee on Banking Supervision	Basel Committee on Banking Supervision	Basel Committee on Banking Supervision
banking supervision	Basel III	Basel III
Basel IV	Basel 3	Basel 3
Basel 4	banking supervision	banking supervision
Basel 2.5	Basel IV	liquidity risk
Basel II.5	Basel 4	liquidity coverage ratio
capital requirements	capital requirements	LCR
Tier 1	Tier 1	net stable funding ratio
additional Tier 1	additional Tier 1	NSFR
Tier 2	Tier 2	liquidity regulation
Incremental default risk	capital conservation buffer	high quality liquid assets
IDR	countercyclical buffer	HQLA
market risk	counterparty credit risk	available stable funding
trading book	central counterparties	ASF
incremental risk charge	credit risk	required stable funding
IRC	securitization framework	RSF
market framework	mortgage insurance	
internal model	standardized approach	
fundamental review of the trading book	margin requirements	
FRTB	internal ratings based approach	
standardized approach	IRBA	
interest rate risk		

This table presents the keywords used to evaluate international media coverage for regulatory announcements of the BCBS for 15 market, 26 credit and 13 liquidity events using LexisNexis.

C Descriptive Statistics

Table C.25: Descriptive Statistics of Independent Variables of the Entire Dataset

	Mean	25%	50%	75%	SD
Panel A: EU					
TIER1_RAT	0.143	0.112	0.136	0.168	0.049
TIER1_RAT^2	0.023	0.013	0.019	0.028	0.018
SEC_ASSET	0.176	0.072	0.146	0.231	0.152
G_SIB	0.162	0	0	0	0.369
LOAN_ASSET	0.561	0.468	0.601	0.684	0.181
PROV_LOAN	0.010	0.002	0.006	0.013	0.030
LCR_PROXY	0.465	0.158	0.285	0.496	0.706
NSFR_PROXY	0.734	0.632	0.754	0.871	0.178
DEP_ASSET	0.529	0.387	0.536	0.671	0.194
GIIPS	0.312	0	0	1	0.464
SIZE	10.763	8.999	11.017	12.712	2.459
COST_INC	0.670	0.514	0.612	0.722	9.266
ROA	0.005	0.002	0.005	0.009	0.015
Panel B: U.S.					
TIER1_RAT	0.134	0.111	0.127	0.147	0.041
TIER1_RAT^2	0.020	0.012	0.016	0.022	0.018
DER_ASSET	0.875	0.0003	0.022	0.112	5.255
G_SIB	0.026	0	0	0	0.159
LOAN_ASSET	0.673	0.613	0.695	0.758	0.129
PROV_LOAN	0.006	0.001	0.002	0.006	0.010
AFF_BANK_c	0.930	1	1	1	0.250
LCR_PROXY	0.349	0.118	0.214	0.400	0.527
NSFR_PROXY	0.945	0.933	0.966	0.985	0.069
DEP_ASSET	0.761	0.722	0.787	0.830	0.107
MOD_AFF_l	0.050	0	0	0	0.230
FULL_AFF_l	0.040	0	0	0	0.190
SIZE	8.600	7.249	8.324	9.486	1.782
COST_INC	0.627	0.546	0.615	0.688	0.334
ROA	0.009	0.007	0.010	0.012	0.009

This table presents descriptive statistics of the independent variables for the entire data set for EU and U.S. banks. TIER1_RAT is the ratio of Tier 1 capital to total risk-weighted assets. SEC_ASSET is the ratio of marketable security investments to total assets. G_SIB is a dummy variable that is 1 for G-SIBs and 0 otherwise. LOAN_ASSET is the ratio of total loans to total assets. PROV_LOAN is the ratio of loan-loss provisions to total loans. LCR_PROXY is a proxy for a bank's LCR. NSFR_PROXY is a proxy for a bank's NSFR. DEP_ASSET is the ratio of customer deposits to total assets. GIIPS is a dummy variable that is 1 for banks located in Greece, Italy, Ireland, Portugal or Spain and 0 otherwise. DER_ASSET is ratio of derivatives to total assets. AFF_BANK_c is a dummy variable that is 1 for U.S. banks that are not subject to the Board's SBHC Policy Statement and 0 otherwise. MOD_AFF_l is a dummy variable that is 1 for U.S. banks that are subject to modified liquidity metrics and 0 otherwise. FULL_AFF_l is a dummy variable that is 1 for U.S. banks that are subject to full liquidity metrics and 0 otherwise. SIZE is the natural logarithm of total assets. COST_INC is the cost-to-income ratio. ROA is the return on assets. More precise descriptive statistics of the dependent variables used in the regressions for market, credit, and liquidity risk for the stock and CDS markets can be provided upon request, as can for the time dummy variables (subprime crisis, global financial crisis, sovereign debt crisis, ex post crisis).

D Market Reactions to BCBS Regulation (Alternative Indices)

Table D.26: Market Reactions to Announcements Regarding Market Risk Regulation

	$\sum \overline{CMAR}_{m\_ew}$	$\sum \overline{CAR}_{m\_ew}$	$\sum \overline{CMAR}_{m\_mw}$	$\sum \overline{CAR}_{m\_mw}$
Panel A: EU				
Actual Events				
Sum (all events)	-0.1442^{**}	-0.1387^{**}	-0.1982^{***}	-0.1970^{***}
p value (all events)	0.016	0.020	0.005	0.003
Sum (market-only events)	-0.0736	-0.0659	-0.0556	-0.0484
p value (market-only events)	0.124	0.146	0.313	0.330
Placebo Events				
Sum (all events)	-0.0298	-0.0296	0.0007	0.0102
p value (all events)	0.606	0.595	0.994	0.881
Sum (market-only events)	-0.0254	-0.0271	-0.0246	-0.0266
p value (market-only events)	0.586	0.551	0.665	0.590
Panel B: U.S.				
Actual Events				
Sum (all events)	0.0258	0.0473	-0.0770	-0.1169
p value (all events)	0.641	0.419	0.454	0.208
Sum (market-only events)	0.0237	0.0571	0.0452	0.0441
p value (market-only events)	0.587	0.192	0.461	0.436
Placebo Events				
Sum (all events)	-0.0294	0.0167	0.0002	0.0394
p value (all events)	0.593	0.750	0.998	0.658
Sum (market- only events)	-0.0186	0.0211	0.0574	0.0522
p value (market-only events)	0.666	0.608	0.342	0.343

	$\sum \overline{\Delta CAS}_{m\_ew}$	$\sum \overline{\Delta CAS}_{m\_mw}$
Panel A: EU		
Actual Events		
Sum (all events)	-0.0578	-0.0506
p value (all events)	0.712	0.776
Sum (market-only events)	-0.1923	-0.2303
p value (market-only events)	0.187	0.154
Placebo Events		
Sum (all events)	0.3487^{**}	0.4805^{**}
p value (all events)	0.046	0.015
Sum (market- only events)	0.2691^{*}	0.3542^{**}
p value (market-only events)	0.066	0.032
Panel B: U.S.		
Actual Events		
Sum (all events)	-0.1896	-0.2043
p value (all events)	0.332	0.328

Sum (market-only events)	-0.1398	-0.1586
p value (market-only events)	0.353	0.326
Placebo Events		
Sum (all events)	0.1876	0.2291
p value (all events)	0.337	0.280
Sum (market-only events)	0.0348	0.0417
p value (market-only events)	0.817	0.780

This table is analogous to Tab. 3. The only difference is that the MSCI Europe and MSCI USA indices were used as proxies for the stock market portfolio, and the abnormal CDS spread changes were calculated using the single-index model.

Table D.27: Determinants of Stock and CDS Market Reactions to Market Risk Regulation

	Stock Market				CDS Market	
	Market Events		Market-Only		Market Events	Market-Only
	CAR	CMAR	CAR	CMAR	ΔCAS	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: EU						
TIER1_RAT	−0.052	0.047	−0.213	0.046	-0.652^{**}	-0.940^{***}
	(0.125)	(0.121)	(0.148)	(0.124)	(0.257)	(0.321)
TIER1_RAT^2	0.089	−0.126	0.606	−0.046		
	(0.248)	(0.255)	(0.404)	(0.345)		
SEC_ASSET	-0.043^{***}	-0.034^{**}	−0.017	−0.007	0.017	0.089^{*}
	(0.017)	(0.017)	(0.016)	(0.016)	(0.049)	(0.051)
G_SIB	0.003	0.003	0.003	0.005	−0.013	−0.019
	(0.012)	(0.010)	(0.006)	(0.006)	(0.020)	(0.025)
GIIPS	-0.015^{***}	-0.015^{***}	-0.026^{***}	-0.021^{***}	−0.005	−0.026
	(0.005)	(0.005)	(0.005)	(0.004)	(0.015)	(0.020)
SOV_DEBT	0.004	−0.005	0.003	−0.004	0.013	−0.001
	(0.005)	(0.005)	(0.004)	(0.005)	(0.010)	(0.013)
GIIPS∗SOV_DEBT	−0.009	−0.007	0.003	0.001	−0.015	−0.006
	(0.007)	(0.007)	(0.007)	(0.007)	(0.011)	(0.012)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	826	826	565	565	268	183
R^2	0.045	0.046	0.033	0.024	0.233	0.138

Panel B: U.S.						
TIER1_RAT	−0.066	−0.055	0.002	0.003	−0.687***	−0.461
	(0.066)	(0.061)	(0.067)	(0.062)	(0.185)	(0.377)
TIER1_RAT^2	0.114	0.105	−0.021	−0.033		
	(0.162)	(0.153)	(0.161)	(0.145)		
DER_ASSET	0.0001	0.0001	−0.00002	−0.0001	0.001***	0.0002
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0004)
G_SIB	−0.011**	−0.011**	−0.004	−0.0005	0.091*	0.185***
	(0.006)	(0.005)	(0.006)	(0.005)	(0.053)	(0.050)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2,919	2,919	1,985	1,985	116	77
R^2	0.071	0.051	0.037	0.034	0.583	0.448

This table is analogous to Tab. 4. The only difference is that the MSCI Europe and MSCI USA indices were used as proxies for the stock market portfolio, and the abnormal CDS spread changes were calculated using the single-index model.

Table D.28: Market Reactions to Announcements Regarding Credit Risk Regulation

	$\sum \overline{CMAR}_{c\_ew}$	$\sum \overline{CAR}_{c\_ew}$	$\sum \overline{CMAR}_{c\_mw}$	$\sum \overline{CAR}_{c\_mw}$
Panel A: EU				
Actual Events				
Sum (all events)	−0.2465***	−0.2334***	−0.4221***	−0.3899***
p value (all events)	0.001	0.005	0.000	0.000
Sum (credit-only events)	-0.0926	-0.085	−0.1717**	−0.1449**
p value (credit-only events)	0.146	0.183	0.027	0.029
Placebo Events				
Sum (all events)	0.0127	0.0264	0.0139	-0.0054
p value (all events)	0.864	0.736	0.900	0.951
Sum (credit-only events)	0.0283	0.0324	-0.0081	-0.0401
p value (credit-only events)	0.645	0.592	0.919	0.546
Panel B: U.S.				
Actual Events				
Sum (all events)	-0.0519	-0.0757	−0.2726*	−0.2851**
p value (all events)	0.439	0.264	0.056	0.023
Sum (credit-only events)	-0.0249	-0.0488	-0.1246	-0.1094
p value (credit-only events)	0.633	0.352	0.163	0.180
Placebo Events				
Sum (all events)	0.0463	0.0748	-0.0094	0.0247
p value (all events)	0.475	0.268	0.937	0.842
Sum (credit-only events)	0.0121	0.0324	-0.0238	-0.0286

p value (credit-only events)	0.809	0.547	0.770	0.697

	$\sum \overline{\Delta CAS}_{c\_ew}$	$\sum \overline{\Delta CAS}_{c\_mw}$
Panel A: EU		
Actual Events		
Sum (all events)	0.3171**	0.3757**
p value (all events)	0.046	0.040
Sum (credit-only events)	0.0798	0.0882
p value (credit-only events)	0.548	0.535
Placebo Events		
Sum (all events)	0.1478	0.1204
p value (all events)	0.370	0.514
Sum (credit-only events)	0.0727	0.072
p value (credit-only events)	0.580	0.614
Panel B: U.S.		
Actual Events		
Sum (all events)	0.4071	0.4627
p value (all events)	0.130	0.100
Sum (credit-only events)	0.2569	0.2858
p value (credit-only events)	0.205	0.185
Placebo Events		
Sum (all events)	0.2942	0.3984
p value (all events)	0.247	0.158
Sum (credit-only events)	0.1999	0.2569
p value (credit-only events)	0.310	0.228

This table is analogous to Tab. 5. The only difference is that the MSCI Europe and MSCI USA indices were used as proxies for the stock market portfolio, and the abnormal CDS spread changes were calculated using the single-index model.

Table D.29: Determinants of Stock and CDS Market Reactions to Credit Risk Regulation

	Stock Market				CDS Market	
	Credit Events		Credit-Only		Credit Events	Credit-Only
	CAR	CMAR	CAR	CMAR	ΔCAS	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: EU						
TIER1_RAT	0.074	0.069	−0.024	−0.014	−0.143*	0.101
	(0.093)	(0.085)	(0.100)	(0.092)	(0.083)	(0.081)
TIER1_RAT^2	−0.249	−0.253	−0.037	−0.121		
	(0.264)	(0.235)	(0.274)	(0.289)		
LOAN_ASSET	−0.025	−0.017	−0.019	−0.032	0.037	0.002

	(0.018)	(0.014)	(0.016)	(0.022)	(0.023)	(0.027)
PROV_LOAN	0.085	0.054	0.045	0.010	−0.586*	−0.858**
	(0.152)	(0.153)	(0.154)	(0.206)	(0.335)	(0.359)
G_SIB	−0.010	−0.009	−0.008	−0.009	0.007	−0.0004
	(0.008)	(0.008)	(0.006)	(0.008)	(0.015)	(0.009)
GIIPS	−0.007	−0.011**	−0.008	−0.011*	0.016*	0.022***
	(0.005)	(0.004)	(0.006)	(0.006)	(0.008)	(0.008)
SOV_DEBT	−0.008***	−0.010***	−0.006**	−0.008***	0.018***	0.016***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.005)	(0.006)
GIIPS∗SOV_DEBT	0.014***	0.015***	0.019***	0.020***	−0.020**	−0.016**
	(0.005)	(0.005)	(0.007)	(0.007)	(0.008)	(0.008)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,510	1,510	1,067	1,067	632	444
R^2	0.027	0.020	0.029	0.017	0.055	0.031
Panel B: U.S.						
TIER1_RAT	0.089*	0.089**	0.092*	0.106**	−0.018	−0.008
	(0.048)	(0.044)	(0.051)	(0.052)	(0.209)	(0.294)
TIER1_RAT^2	−0.220*	−0.216**	−0.219*	−0.267**		
	(0.121)	(0.107)	(0.132)	(0.131)		
LOAN_ASSET	−0.001	−0.001	−0.001	0.001	−0.029	0.013
	(0.006)	(0.004)	(0.007)	(0.008)	(0.051)	(0.024)
PROV_LOAN	−0.079	−0.085	−0.229**	−0.198*	0.357	0.420**
	(0.083)	(0.077)	(0.108)	(0.116)	(0.274)	(0.183)
G_SIB	−0.006*	−0.004	−0.0002	0.003	0.031	0.031
	(0.004)	(0.003)	(0.004)	(0.004)	(0.033)	(0.021)
AFF_BANK_c	−0.003	−0.007***	0.001	−0.005***		
	(0.002)	(0.002)	(0.002)	(0.002)		
Control	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	5,388	5,388	3,732	3,732	207	143
R^2	0.023	0.017	0.052	0.025	0.103	0.129

This table is analogous to Tab. 6. The only difference is that the MSCI Europe and MSCI USA indices were used as proxies for the stock market portfolio, and the abnormal CDS spread changes were calculated using the single-index model.

Table D.30: Market Reactions to Announcements Regarding Liquidity Risk Regulation

	$\sum \overline{CMAR}_{l\_ew}$	$\sum \overline{CAR}_{l\_ew}$	$\sum \overline{CMAR}_{l\_mw}$	$\sum \overline{CAR}_{l\_mw}$
Panel A: EU				
Actual Events				
Sum (all events)	-0.0761	-0.0483	-0.0961	-0.0683
p value (all events)	0.169	0.350	0.168	0.259
Sum (liquidity-only events)	-0.0152	0.0041	0.0086	0.0151
p value (liquidity-only events)	0.751	0.932	0.868	0.745
Placebo Events				
Sum (all events)	-0.0304	-0.0352	0.0047	-0.0203
p value (all events)	0.566	0.493	0.932	0.756
Sum (liquidity-only events)	-0.0140	-0.0162	0.0098	0.0022
p value (liquidity-only events)	0.772	0.733	0.852	0.961
Panel B: U.S.				
Actual Events				
Sum (all events)	-0.0075	0.0002	0.0490	0.0491
p value (all events)	0.880	0.997	0.617	0.592
Sum (liquidity-only events)	-0.0163	-0.0122	0.0626	0.0467
p value (liquidity-only events)	0.684	0.765	0.414	0.494
Placebo Events				
Sum (all events)	0.0282	0.0477	0.1310	0.1049
p value (all events)	0.603	0.377	0.223	0.265
Sum (liquidity-only events)	0.0188	0.0253	0.0546	0.0358
p value (liquidity-only events)	0.650	0.564	0.465	0.607

	$\sum \overline{\Delta CAS}_{l\_ew}$	$\sum \overline{\Delta CAS}_{l\_mw}$
Panel A: EU		
Actual Events		
Sum (all events)	0.1566	0.0865
p value (all events)	0.346	0.650
Sum (liquidity-only events)	-0.0002	-0.0500
p value (liquidity-only events)	0.999	0.737
Placebo Events		
Sum (all events)	0.0950	0.0466
p value (all events)	0.578	0.815
Sum (liquidity-only events)	0.0711	0.0251
p value (liquidity-only events)	0.602	0.863
Panel B: U.S.		
Actual Events		
Sum (all events)	0.4139^{*}	0.1256^{***}
p value (all events)	0.051	0.007
Sum (liquidity-only events)	0.1952	0.0745^{*}
p value (liquidity-only events)	0.196	0.068

Placebo Events		
Sum (all events)	-0.0298	-0.0476
p value (all events)	0.833	0.217
Sum (liquidity-only events)	0.0638	-0.0226
p value (liquidity-only events)	0.609	0.425

This table is analogous to Tab. 7. The only difference is that the MSCI Europe and MSCI USA indices were used as proxies for the stock market portfolio, and the abnormal CDS spread changes were calculated using the single-index model.

Table D.31: Determinants of Stock and CDS Market Reactions to Liquidity Risk Regulation

	Stock Market				CDS Market	
	Liquidity Events		Liquidity-Only		Liquidity Events	*Liquidity-Only*
	CAR	CMAR	CAR	CMAR	ΔCAS	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: EU						
LCR_PROXY	−0.0002	0.0001	−0.001	−0.001	−0.037***	−0.037***
	(0.001)	(0.001)	(0.004)	(0.003)	(0.010)	(0.011)
NSFR_PROXY	−0.012	−0.016	−0.032	−0.033*	0.040	0.006
	(0.012)	(0.013)	(0.021)	(0.017)	(0.047)	(0.035)
DEP_ASSET	−0.022	−0.024	−0.013	−0.004	−0.089**	0.040
	(0.015)	(0.017)	(0.022)	(0.019)	(0.041)	(0.049)
GIIPS	0.006	0.005	0.008	0.011**	−0.008	−0.023***
	(0.003)	(0.004)	(0.006)	(0.006)	(0.007)	(0.008)
SOV_DEBT	−0.025***	−0.023***	−0.024***	−0.021***	0.053***	0.030***
	(0.005)	(0.005)	(0.007)	(0.007)	(0.008)	(0.007)
GIIPS∗SOV_DEBT	−0.025***	−0.026***	−0.046***	−0.047***	−0.008	0.041***
	(0.008)	(0.008)	(0.012)	(0.012)	(0.012)	(0.010)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	702	702	480	480	177	118
R^2	0.107	0.095	0.124	0.115	0.326	0.379
Panel B: U.S.						
MOD_AFF_1	−0.151	−0.147	−0.145	−0.173		
	(0.119)	(0.123)	(0.136)	(0.142)		
FULL_AFF_1	0.093**	0.126***	0.198***	0.228***		
	(0.041)	(0.041)	(0.065)	(0.072)		

LCR_PROXY	−0.00004	0.0004	0.001	0.002
	(0.003)	(0.002)	(0.003)	(0.003)
NSFR_PROXY	−0.014	−0.028	−0.021	−0.033
	(0.022)	(0.021)	(0.026)	(0.025)
DEP_ASSET	0.005	0.006	−0.014	−0.006
	(0.017)	(0.017)	(0.020)	(0.019)
MOD_AFF_l∗LCR_PROXY	−0.025	−0.040*	−0.023	−0.035
	(0.022)	(0.024)	(0.028)	(0.032)
FULL_AFF_l∗LCR_PROXY	−0.034***	−0.040***	−0.034***	−0.039***
	(0.007)	(0.007)	(0.009)	(0.009)
MOD_AFF_l∗NSFR_PROXY	0.165	0.165	0.164	0.195
	(0.128)	(0.133)	(0.149)	(0.156)
FULL_AFF_l∗NSFR_PROXY	−0.099**	−0.136***	−0.214***	−0.253***
	(0.049)	(0.048)	(0.077)	(0.085)
Control	Yes	Yes	Yes	Yes
Obs.	2,629	2,629	1,818	1,818
R^2	0.028	0.032	0.085	0.067

This table is analogous to Tab. 8. The only difference is that the MSCI Europe and MSCI USA indices were used as proxies for the stock market portfolio, and the abnormal CDS spread changes were calculated using the single-index model.

E Estimating the Standard Deviation of Prediction Errors

Event period standardized abnormal returns and CDS spread changes are calculated by dividing these values by their estimated standard deviation, which accounts for the fact that abnormal returns and CDS spread changes are prediction errors. The test statistics of Boehmer et al. (1991) and Corrado and Zivney (1992) assume that the prediction error is calculated using the market model. However, abnormal CDS spread changes are estimated using a model with four regressors. While the mechanics for calculating the standard deviation of (cumulative) abnormal CDS spread changes remain consistent, there are variations compared to the market model. Following Theil (1971) and Campbell et al. (1997), the covariance matrix of the prediction error estimated by a simple linear regression, e.g. the market model, is given by

$$\boldsymbol{V}_i = \mathbf{I}\sigma_{\epsilon_i}^2 + \boldsymbol{X}_i^*(\boldsymbol{X}_i'\boldsymbol{X}_i)^{-1}\boldsymbol{X}_i^{*\prime}\sigma_{\epsilon_i}^2, \tag{E.31}$$

where $\mathbf{I}$ is the $(T_s \times T_s)$ identity matrix and $\boldsymbol{X}_i^*$ is a $(T_s \times 2)$ matrix with a vector of ones in the first column and a vector of $R_{m,t}$ in the second column in the event period. The variance of the error term is denoted by $\sigma_{\epsilon_i}^2$, while $\boldsymbol{X}_i$ is a $(T \times 2)$ matrix in the estimation period with a vector of ones in the first column and the vector of $R_{m,t}$ in the second column. The variance of the prediction error consists of two parts, namely the variance due to future disturbances (first term) and the additional variance due to the sampling error (second term). As the length T of the estimation window increases, the variance due to the sampling error converges to zero. In this regard, the 150-day estimation window contributes to reducing variance.

The variance of the cumulative prediction error (CPE) is then given by

$$\mathrm{Var}[CPE_i(t_1, t_2)] = \boldsymbol{\lambda}'\boldsymbol{V}_i\boldsymbol{\lambda}, \tag{E.32}$$

where $\boldsymbol{\lambda}$ is a $(T_s \times 1)$ vector with ones. Given the market model is used to estimate abnormal returns, the standard deviation of $CAR_i(t_1, t_2)$ can be calculated with the denominator in Eq. (19). However, abnormal CDS spread changes are estimated using a four-factor model (Eq. (14)), implying that the dimensions of $\boldsymbol{X}_i^*$ and $\boldsymbol{X}_i$ change. Hence, $\boldsymbol{X}_i^*$ is a $(T_s \times 5)$ matrix of event period values with a vector of ones in the first column, a vector of $\Delta S_{index,t}$ in the second column, a vector of $Level_t$ in the third column, a vector of $Slope_t$ in the fourth column and a vector of $\Delta Vola_t$ in the fifth column. While $\boldsymbol{X}_i^*$ contains the event period values, $\boldsymbol{X}_i$ is a $(T \times 5)$ matrix with the same columns, but includes the estimation period values.

Abnormal CDS spread changes are standardized by the respective standard deviation derived from the variance explained above.

F Monetary Shocks

Table F.32: Factors of the Press Release and Press Conference Window for each ECB Announcement

Date	Press Release	Press Conference			
	$target_t^E$	$timing_t$	FG_t	QE_t	$path\_conf_t$
2022-04-14	-0.568	-0.678	-2.140	5.133	2.314
2022-06-09	-2.245	-1.602	2.134	-3.394	-2.862
2022-07-21	3.691	-1.177	-0.439	-7.523	-9.139
2022-09-08	6.316	2.680	-0.722	-1.108	0.850
2022-10-27	2.616	-0.197	0.122	-3.687	-3.762
2022-12-15	-4.875	0.215	13.203	1.600	15.018
2023-02-02	0.548	-0.960	-1.248	-1.881	-4.089
2023-03-16	21.120	-0.940	6.825	3.660	9.544
2023-05-04	-4.989	-0.067	-0.103	0.300	0.130
2023-06-15	-0.335	0.489	-0.803	-5.772	-6.086
2023-07-27	-0.297	-0.758	-0.393	-1.331	-2.483
2023-09-14	7.129	0.402	-0.767	-0.113	-0.478
2023-10-26	-1.319	0.617	-2.167	-1.905	-3.455

This table presents the calculated monetary policy shocks for each ECB announcement. The factors are computed using the EA-MPD provided by Altavilla et al. (2019), as described in Sec. 3.4.4.

Table F.33: Factors for each Fed Announcement

Date	$target_t^F$	$path_t$
2022-01-26	-0.002	0.0002
2022-03-16	-0.027	0.304
2022-05-04	-0.018	-0.056
2022-06-15	0.040	0.123
2022-07-27	-0.015	0.035
2022-09-21	-0.037	0.299
2022-11-02	-0.010	-0.145
2022-12-14	0.003	0.197
2023-02-01	-0.004	0.060
2023-03-22	0.059	-0.210
2023-05-03	0.023	0.025
2023-06-14	-0.014	0.262
2023-07-26	0.002	0.024
2023-09-20	-0.004	0.191
2023-11-01	-0.005	-0.012
2023-12-13	0.017	-0.238

This tables presents the monetary policy shocks for each Fed announcement. The factors are provided by Acosta et al. (2024), as described in Sec. 3.4.4.

G Market Reactions to Fed and ECB Events (Alternative Indices)

Table G.34: U.S. Stock Market Reactions to Fed and ECB Announcements

	Banks: $\overline{CAR}(t_1, t_2)$				Insurers: $\overline{CAR}(t_1, t_2)$			
Fed	(-1;0)	(-1;+1)	(0;0)	(0;+1)	(-1;0)	(-1;+1)	(0;0)	(0;+1)
2022-01-26	0.003	-0.005	-0.006	-0.015	0.006	-0.006	-0.005	-0.017
	312	310	314	311	84	84	84	84
2022-03-16	-0.011	-0.022	0.002	-0.009	-0.001	0.004	0.003	0.008
	321	318	322	318	84	83	84	83
2022-05-04	0.006	0.006	0.003	0.002	0.002	0.017	-0.003	0.012
	320	317	320	317	83	83	83	83
2022-06-15	0.005	0.001	0.002	-0.002	-0.005	-0.014	-0.01	-0.019 (∗|∗)
	324	322	326	323	82	81	83	82
2022-07-27	0.007	-0.002	0.001	-0.007	-0.018	-0.026	-0.016	-0.024 (|∗∗)
	316	312	319	315	82	81	82	81
2022-09-21	0.009	0	0.004	-0.004	-0.004	-0.019 (∗|∗)	-0.009	-0.013
	323	323	324	324	80	80	81	80
2022-11-02	0.003	0.004	0	0.001	0.009	-0.001	0.004	-0.006
	320	311	320	311	81	81	81	81
2022-12-14	-0.022 (∗|∗∗)	-0.025 (∗|∗)	-0.012 (|∗)	-0.015	-0.002	0.005	-0.002	0.005
	326	324	330	328	79	79	79	79
2023-02-01	0.011	0.019	0.001	0.009	0.004	0	-0.003	-0.006
	324	321	329	324	80	80	80	80
2023-03-22	-0.001	-0.023 (∗|)	-0.025 (∗∗∗|∗∗)	-0.047 (∗∗∗|∗∗∗)	0.003	-0.014	-0.011 (∗∗|∗∗)	-0.029 (∗∗|∗∗∗)
	332	332	333	333	81	81	81	81
2023-05-03	-0.045 (|∗)	-0.07 (∗|∗∗)	-0.003	-0.028	-0.002	-0.006	0.009	0.005
	340	340	340	340	79	79	80	80
2023-06-14	0.001	0.008	-0.015	-0.008	-0.02	-0.024	-0.016 (∗∗|∗∗)	-0.021
	335	334	338	336	79	79	80	80
2023-07-26	0.029	0.032	0.033 (∗|∗∗)	0.036 (|∗)	0.003	-0.002	0.01 (|∗)	0.004
	329	327	333	331	79	78	80	79
2023-09-20	0.008	0.025	0.008	0.024 (|∗)	0.016 (|∗∗)	0.021 (|∗∗)	0.007	0.013
	335	330	339	333	80	80	80	80
2023-11-01	-0.02	-0.004	-0.016	0	0.005	0.012	0.003	0.011
	332	331	337	336	81	81	81	81
2023-12-13	0.022	0.049	0.033 (|∗)	0.06 (∗∗|∗∗)	0.002	-0.01	0.002	-0.009
	344	343	346	345	83	83	83	83
ECB								
2022-04-14	0.001	-	-0.001	-	0.005	-	0.006	-
	316	0	318	0	84	0	84	0
2022-06-09	-0.012	-0.016	-0.008	-0.012	-0.001	-0.003	0.002	0
	316	313	316	313	83	82	83	82
2022-07-21	-0.001	0	-0.005	-0.005	-0.009	-0.013	-0.006	-0.016
	312	309	316	310	80	79	81	80
2022-09-08	0.007	0.009	0.004	0.006	0.013	0.007	0.002	-0.005
	321	319	323	321	82	82	82	82
2022-10-27	0.014	0.022	0.009	0.017	0.022 (|∗)	0.029 (|∗∗)	0.012	0.019 (|∗∗)
	313	310	322	317	81	80	81	80
2022-12-15	-0.015	-0.009	-0.003	0.003	0.005	0.011	0.007	0.013
	329	328	333	332	79	79	79	79
2023-02-02	0.009	0.02 (∗|∗)	0.008	0.019 (∗∗|∗∗)	-0.006	0.001	-0.003	0.004
	324	324	328	328	80	80	80	80

2023-03-16	0.014	-0.023	0.018 (*|*)	-0.019	-0.011	-0.043 (**|**)	0.009	-0.023 (*|)
	333	333	333	333	80	80	80	80
2023-05-04	-0.028	-0.004	-0.025 (|*)	0	0.005	0.012	-0.003	0.003
	340	339	341	340	80	80	81	81
2023-06-15	-0.008	-0.005	0.007	0.009	-0.021	-0.019	-0.005	-0.003
	336	332	338	334	80	80	80	80
2023-07-27	0.036 (|*)	0.036	0.003	0.003	0.004	-0.004	-0.005	-0.014
	330	327	336	333	79	79	79	79
2023-09-14	0.001	0.014	0.01	0.023	-0.004	0.007	0.005	0.015
	338	338	339	338	80	80	80	80
2023-10-26	0.06 (*|**)	0.058 (|*)	0.039 (*|**)	0.038	0.023 (*|**)	0.009	0.012	-0.002
	329	326	334	330	78	77	80	79
2023-12-14	0.06 (*|**)	0.067 (*|**)	0.027	0.033	-0.009	-0.024 (|*)	-0.011	-0.027 (*|**)
	345	342	345	342	83	83	83	83

This table presents $\overline{CAR}(t_1, t_2)$ for U.S. banks and insurers in response to interest rate decisions by the Fed and the ECB, measured across different event windows. Values are rounded to the third decimal place and calculated according to Eqs. (13), (15) and (17). Statistical significance is assessed using the parametric test of Boehmer et al. (1991), adjusted by Kolari and Pynnönen (2010), and the nonparametric test of Corrado and Zivney (1992). The corresponding p values are based on a two-sided significance test: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. The first value in parentheses indicates the significance of the parametric test; the second refers to the nonparametric test. The number below each result indicates the portfolio size. The MSCI USA is used as proxy for the stock market porfolio.

Table G.35: Eurozone Stock Market Reactions to Fed and ECB Announcements

	Banks: $\overline{CAR}(t_1, t_2)$				Insurers: $\overline{CAR}(t_1, t_2)$			
Fed	(-1;0)	(-1;+1)	(0;0)	(0;+1)	(-1;0)	(-1;+1)	(0;0)	(0;+1)
2022-03-16	0.019 (*|*)	0.007	0.015 (|*)	0.002	0.004	-0.009	0.005	-0.007
	71	71	71	71	26	26	26	26
2022-05-04	0.01	0.006	0.005	0.001	0.012 (*|*)	-0.003	0.004	-0.009
	59	59	71	71	24	24	27	27
2022-06-15	0.013	0.021	0	0.004	0.022 (**|***)	0.021 (*|**)	0.011 (|*)	0.01
	65	63	72	70	27	27	27	27
2022-07-27	0	-0.01	0.007	-0.003	0	-0.013	0.002	-0.011
	72	72	72	72	28	28	28	28
2022-09-21	-0.016	0.005	-0.017	0.004	-0.011	-0.001	-0.007	0.003
	70	70	71	71	28	28	28	28
2022-11-02	0.009	0.017	0.004	0.012	-0.002	0.011	-0.005	0.007
	66	66	66	66	25	25	25	25
2022-12-14	0.006	0.012	0.002	0.009	-0.006	0.002	-0.001	0.007
	69	69	69	69	28	28	28	28
2023-02-01	0.011	0	0.006	-0.005	0.004	-0.001	0.001	-0.003
	69	69	69	69	27	27	27	27
2023-03-22	0.007	-0.004	-0.012 (*|**)	-0.024 (**|***)	0.006	0.002	-0.01 (**|**)	-0.013 (**|**)
	69	69	69	69	26	26	26	26
2023-05-03	-	-	-0.004	-0.011	-	-	0.003	-0.005
	0	0	68	68	0	0	24	24
2023-06-14	-0.001	-0.001	0.003	0.003	-0.003	-0.008	0.001	-0.005
	69	69	69	69	27	27	27	27
2023-07-26	0.003	-0.009	0.005	-0.007	0.005	-0.002	0.005 (*|*)	-0.002
	71	71	71	71	28	28	28	28
2023-09-20	0.001	0.011	-0.003	0.008	-0.006	0	-0.007	0
	71	70	71	70	28	28	28	28
2023-11-01	-0.004	-0.007	-0.001	-0.004	0	-0.006	0	-0.005

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<tr><td>2023-03-16</td><td>-0.047 (***|***)</td><td>-0.059 (***|***)</td><td>-0.008</td><td>-0.019 (*|*)</td><td>-0.016 (*|)</td><td>-0.03 (**|**)</td><td>0.003</td><td>-0.01</td></tr>
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<tr><td>2023-10-26</td><td>0.002</td><td>0.009</td><td>0.005</td><td>0.011 (|*)</td><td>-0.002</td><td>0.001</td><td>-0.001</td><td>0.002</td></tr>
<tr><td></td><td>67</td><td>67</td><td>67</td><td>67</td><td>26</td><td>26</td><td>26</td><td>26</td></tr>
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<tr><td></td><td>70</td><td>70</td><td>70</td><td>70</td><td>28</td><td>28</td><td>28</td><td>28</td></tr>
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This table presents $\overline{CAR}(t_1, t_2)$ for Eurozone banks and insurers in response to interest rate decisions by the Fed and the ECB, measured across different event windows. Values are rounded to the third decimal place and calculated according to Eqs. (13), (15) and (17). Statistical significance is assessed using the parametric test of Boehmer et al. (1991), adjusted by Kolari and Pynnönen (2010), and the nonparametric test of Corrado and Zivney (1992). The corresponding p values are based on a two-sided significance test: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. The first value in parentheses indicates the significance of the parametric test; the second refers to the nonparametric test. The number below each result indicates the portfolio size. The MSCI Europe is used as proxy for the stock market porfolio.

H Stable Distribution—The Tail Parameter α

The analyses in Börner et al. (2025) show that a family of SDIs is the most promising option for modeling the distribution of the returns of CCs. Therefore, this family of functions is also used in the present study and is introduced here in detail. Several different parametrizations exist for the SDI. In the following formulation, we follow the presentation and the parametrization of the SDI described in Nolan (2020, Def. 1.4 therein).

SDIs are a class of probability distributions suitable for modeling heavy-tailed and skewed distributions. A linear combination of two independent, identically distributed stable random variables has the same distribution as the individual variables. A random variable X has the SDI $SDI(\alpha, \beta, \gamma, \delta)$ if its characteristic function is given by

$$\mathrm{E}\left[\exp\left(\mathrm{i}\mathrm{t}X\right)\right] = \begin{cases} \exp\left(\mathrm{i}\delta\mathrm{t} - |\gamma\mathrm{t}|^{\alpha}\left[1 + \mathrm{i}\beta\mathrm{sign}(\mathrm{t})\ \tan\left(\frac{\pi\alpha}{2}\right)\left(|\gamma\mathrm{t}|^{1-\alpha} - 1\right)\right]\right) & \alpha \neq 1 \\ \exp\left(\mathrm{i}\delta\mathrm{t} - |\gamma\mathrm{t}|\ \left[1 + \mathrm{i}\beta\mathrm{sign}(\mathrm{t})\ \frac{2}{\pi}\ln\left(|\gamma\mathrm{t}|\right)\right]\right) & \alpha = 1. \end{cases} \tag{H.33}$$

The first parameter $0 < \alpha \leq 2$ is called the shape parameter and describes the tail of the distribution. Sometimes this parameter is also denoted as the *tail parameter*, *index of stability* or *characteristic exponent*. The second parameter $-1 \leq \beta \leq +1$ is the skewness parameter. If $\beta = 0$, then the distribution is symmetric; otherwise, it is left-skewed ($\beta < 0$) or right-skewed ($\beta > 0$). When α is small, the skewness of β is significant. As α increases, the effect of β decreases. Further, $\gamma \in \mathbb{R}^{+}$ is called the scale parameter, and $\delta \in \mathbb{R}$ is the location parameter.

For the special case of $\alpha = 2$, the characteristic function given by Eq. (H.33) reduces to $\mathrm{E}\left[\exp\left(\mathrm{i}tX\right)\right] = \exp\left(\mathrm{i}\delta t - (\gamma t)^{2}\right)$ and becomes independent of the skewness parameter β, and the SDI is equal to a normal distribution with mean δ and standard deviation $\sigma = \sqrt{2}\gamma$. This is an important property for portfolio theory, for example, when considering multivariate distributions. The rationale is that it is basically possible to model the normally distributed components of a random vector with the same function class.

In the main part, the tail parameter α is estimated for each year under consideration on a weekly return basis and used as input data for the DTW distance analysis.

I Modeling with Radial Basis Functions

In many scientific fields (Powell, 1977; Poggio and Girosi, 1990; Sahin, 1997; Biancolini, 2017), RBFs are used to carry out a function approximation of the following form

$$y(\mathbf{x}) = \sum_{w=1}^{W} \lambda_w \, \phi(\|\mathbf{x} - \mathbf{x}_w\|), \tag{I.34}$$

where $y(\mathbf{x})$ is a one-dimensional function depending on $\mathbf{x} \in \mathbb{R}^n$. The function $y(\mathbf{x})$ is modeled as a sum of W RBFs, each centered at a different center $\mathbf{x}_w$ and weighted with an appropriate coefficient λ_w. The real value of every RBF is strictly positive and depends only on the distance between the point $\mathbf{x}$ and the center $\mathbf{x}_w$. The distance $r_{rb} = \|\mathbf{x} - \mathbf{x}_w\|$ is determined in a previously defined norm. We only use the Euclidean distance as the norm in our analyses.

To model and reconstruct the height profile over the distance matrix $\mathbf{D}$ in Sec. 4.5, we use RBFs of Gaussian type

$$\phi(r) = \exp\left(-a r_{rb}^2\right) \tag{I.35}$$

with infinite support and a positive shape parameter a. The latter can also be interpreted as the effective range of the RBF. If R_{rb} denotes the distance between two different centers and $0 < p_{rb} < 1$ denotes the desired residual effect at the next center, then the area of effect can be set by a due to $a = -R_{rb}^{-2} \ln p_{rb}$.

The parameter vector $\boldsymbol{\lambda}_{rb}$ is determined using a least squares approach. In some applications, we find that a least squares fit encounters problems with ill-conditioned matrices. Therefore, we extend our Lagrange function to be minimized by a regularization term. The latter term is also referred to as cost-functional and takes into account the costs of the deviation from a smooth function. The theoretical foundations of this approach can be traced back to earlier work by Tikhonov (1943, 1963). The implemented regularization procedure is currently standard (Poggio and Girosi, 1990), cf. also Sahin (1997); Biancolini (2017) and the substantial amount of literature cited therein.

Hence, we set the Lagrange function

$$\mathcal{L} = \sigma_{rb}^2 + \alpha_{rb} \boldsymbol{\lambda}_{rb}' \boldsymbol{\lambda}_{rb}, \tag{I.36}$$

where σ_{rb}^2 is the squared error between the modeled ($\hat{y}_i$) and sample (y_i) values for $i = 1, \ldots, N$ with sample length N. Furthermore, α_{rb} is a positive real number called the regularization parameter. If $\alpha_{rb} \rightarrow 0$, the problem is unconstrained, and the resulting model can be completely determined from the sample. On the other hand, if $\alpha_{rb} \rightarrow \infty$, the a priori desired smoothness of the resulting model dominates and leads to a highly smooth function, nearly flat in the limit and almost independent of the measured sample.

Finally, the solution to the minimization problem given by Eq. (I.36) is

$$\lambda_{rb} = \left(\mathbf{\Phi} + \frac{\alpha_{rb}}{N}\mathbf{E}\right)^{-1} \mathbf{v}. \tag{I.37}$$

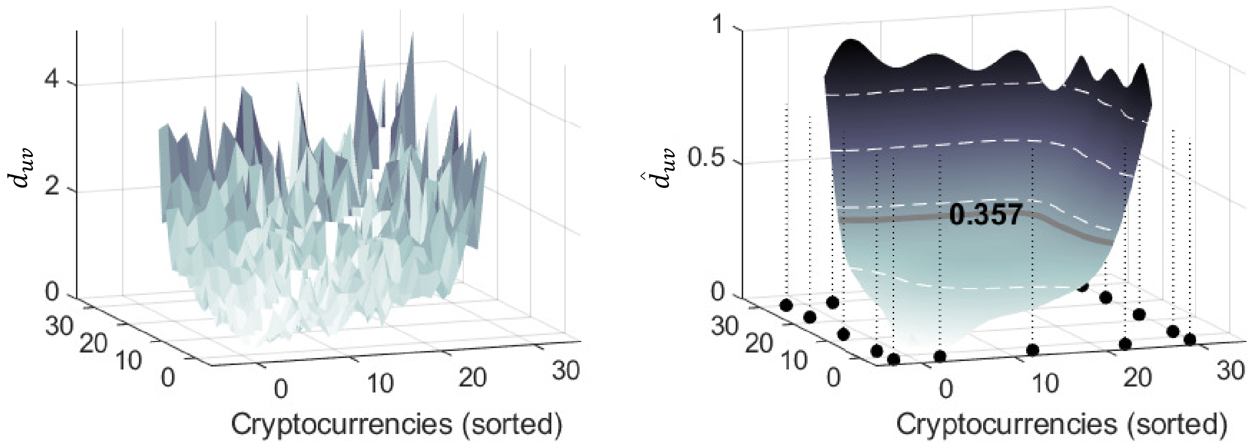
Abbreviating $\phi_{iw} = \phi(\|\mathbf{x}_i - \mathbf{x}_w\|)$ as the value of the w-th RBF at the sample point $\mathbf{x}_i$ for $i = 1, \ldots, N$ and given the output y_i, then the vector $\mathbf{v} = (\langle y_i \phi_{iw} \rangle)_{w=1,\ldots,W}$ and matrix $\mathbf{\Phi} = (\langle \phi_{ik}\phi_{iw} \rangle)_{k,w=1,\ldots,W}$, where $\langle\cdot\rangle$ denotes the sample average. Further, $\mathbf{E}$ denotes the identity matrix in $\mathbb{R}^{W\times W}$.

In practice, in very few applications do we assign successively increasing values $0 \leq \alpha_{rb} < 100$ to the regularization parameter until the observable local roughness or heavily peaked structure of the modeled surface vanishes. We observe that the height profile of the distance matrix $\mathbf{D}$ remains well reconstructed, but modeling the absolute height worsens with the increasing influence of regularization. The modeling properties improve if a constant term is incrementally added to the model given in Eq. (I.34). The solution expressed by Eq. (I.37) does not change if the number of RBFs is increased only by 1, $W \to W + 1$, and the value identical to 1 is assigned to the first RBF, $\phi_1 = 1$ for all $\mathbf{x} \in \mathbb{R}^n$, while the changes are considered in the elements of the vector $\mathbf{v}$ and matrix $\mathbf{\Phi}$.

The majority of the analyses could be carried out with $\alpha_{rb} = 0$ and led without regularization procedures to very good results. For the results shown in the main part, we do not apply the regularization procedure.

In Fig. I.6, an example of the modeling process with RBFs and $\alpha_{rb} = 0$ is shown. The left figure shows the rough and peaked height structure d_{uv} above the DTW distance matrix $\mathbf{D}_{\mathrm{SE}}$ calculated in Sec. 4.5. It is the three-dimensional counterpart of the upper-right panel of Fig. 4 viewed from the upper-left corner along the main diagonal. The graphic on the right shows the surface of the standardized height structure $\hat{d}_{uv}$ modeled with RBFs. Some contour lines (dashed white) are also shown, each with a distance of 0.2 units. The contour of the threshold $d_{\mathrm{bound}} = 0.357$ for the squared Euclidean metric is shown in light gray, cf. Sec. 4.5. The bullet points and the corresponding vertical dashed lines illustrate the centers and positions of the RBFs, respectively.

Figure I.6: DTW Distance and Normalized RBF Model



An explicit and detailed representation of the modeling process leading to the segmentation of the CC market in Sec. 4.5. The DTW distances are based on the squared Euclidean metric.

Declaration of Generative AI and AI-assisted Technologies

During the preparation of this dissertation, the author used ChatGPT to improve the language and readability of the text, and to assist with coding in the programming language R and with document preparation in LaTeX. In addition, DeepL was used for translation purposes. All content generated or edited with the help of these tools was reviewed and revised by the author, who takes full responsibility for the final version of the publication.

Düsseldorf, July 9, 2025

Jonas Krettek

Statutory Declaration in Lieu of an Oath

I, Jonas Krettek, declare in lieu of an oath, that the Dissertation in hand has been prepared by me independently and without unauthorized outside assistance, in compliance with the “Regulations on the Principles for Ensuring Good Scientific Practice at Heinrich Heine University Düsseldorf”.

Düsseldorf, July 9, 2025

Jonas Krettek