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Stress-testing net trading income: The case of European banks

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Stress-testing net trading income: the case of European banks

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Abstract

Net trading income is an important but volatile source of income for many euro area banks, highly sensitive to changes in financial market conditions. Using a representative sample of European banks, we study the distribution of net trading income (normalized by total assets) conditional to changes in key macro-financial risk factors. To map the linkages of net trading income with financial risk factors and capture non-linear effects, we implement a dynamic fixed effects quantile model using the method of moments approach. We use the model to empirically estimate and forecast the conditional net trading income distribution from which we quantify tail risk measures and expected losses across banks. We find a heterogeneous and asymmetric impact of the risk factors on the distribution of net trading income. Credit and interest rate spreads affect lower quantiles of the net trading income distribution while stock returns are an important determinant of the upper quantiles. We also find that the onset of the Covid-19 pandemic resulted in a significant increase in the 5th and 10th percentile expected capital shortfall. Moreover, adverse scenario forecasts show a wide dispersion of losses and a long-left tail is evident especially in the most severe scenarios. Our findings highlight strong inter-linkages between financial risk factors and trading income and suggest that this tractable methodology is ideal for use as an additional tool in stress test exercises.

Keywords: Stress testing, net trading income, quantile panel regression, capital shortfall

JEL Codes: C21, C23, G21, G28

Non-Technical Summary

Since 2014, a large share of banks' net operating income in the euro area arises from non-interest income activities where net fee and commission income (NFCI) and net trading income (NTI) are the most important contributors. Diversification of income sources can have unintended consequences, it can create new risks and challenges for the banking sector.

From a regulatory and supervisory perspective, quantifying and modelling of these balance sheet items' evolution in a stress scenario remains a relevant and unmet need. Modelling non-interest related sources for stress-test purposes is not straightforward as the source of risks and the channel of transmission might differ from the one already investigated in the literature. For instance, trading income is likely to be much more volatile and responsive to financial developments while credit risk is related to slow moving macro variables.

This paper seeks to fill this void by empirically estimating the linkages between financial risk factors and net trading income. We focus on net trading income as it is the most volatile and riskiest of all the non-interest income activities. We find a strong and asymmetric impact of the risk factors on the tails of the distribution of NTI over total assets (NTI/TA). In particular, long term interest rates, credit spreads and oil returns exhibit a strong positive effect on the lower quantiles of the NTI/TA distribution, an effect that dissipates over higher quantiles. On the other hand, stock returns have a significant (positive) effect only on the right tail of the NTI/TA distribution. We also find that bank specific characteristics such as the amount of risk weighted assets and the total equity the bank hold is a poor indicator of NTI/TA performance across quantiles.

The volatile nature of trading income can lead to increased downside tail risk, that is, the risk that a bank experiences an extreme trading loss. Extreme returns cause "fatter" tails than a normal distribution would predict. Inter-linkages between financial risk factors and trading income indicate that financial crisis and adverse market shocks can produce left tail events which could have a damaging impact on the trading portfolio. We employ the estimated cumulative distribution function to gauge the (time-varying) conditional expected shortfall of capital at different time horizons and across banks. Using expected capital shortfall (see Acharya et al., 2012) we can quantify the tail risk as the expected loss conditional

on the bank experiencing an extreme event (a loss greater than the 5th or 10th percentile for example). We find that at the onset of the Covid-19 pandemic the expected CET1 ratio shortfall due to trading income losses at the 5th percentile ranges between -15 and -100 basis points with all banks exceeding what could be considered a material loss.

One of the objectives of stress-test models is to forecast of banks' balance-sheet items under different hypothetical stress scenarios. The severity of the stress scenarios is directly related to the realizations of the market risk factors. In this respect, our stress scenarios can be calibrated to the respective quantiles of the risk factors giving a clear and intuitive interpretation of the scenario and the implied loss distribution. We use the model to deliver multi-steps forecasts of NTI/TA for banks for various quantiles that reflect different degree in the severity of the scenario.

1 Introduction

In recent years, a growing literature emerged on the importance, design and implications of stress-tests as a tool to assess the resilience of the financial system (V. Acharya, Engle, and Richardson (2012); Covas, Rump, and Zakrajšek (2014); V. Acharya, Engle, and Pierret (2014); Coffinet, Lin, and Martin (2009); Lehmann, Manz, et al. (2006); Albertazzi and Gambacorta (2009); Schuermann (2014)). Most of the contributions quantify the impact of adverse macroeconomic scenarios in terms of capital shortfall, risk weighted assets (V. Acharya, Engle, and Pierret (2014), V. Acharya, Engle, and Richardson (2012)) or the most relevant source of bank's revenue - net-interest income (V. V. Acharya, Berger, and Roman (2018)). However, market deregulation and the protracted period of low interest rates in the aftermath of the 2007-09 financial crisis induced banks to diversify away from interest-related earnings. In the euro area, around 40%¹ of banks overall net operating income arises from non-interest income²³ activities with net fee and commission income (NFCI) and net trading income (NTI) to be the most important⁴.

The increasing importance of NTI and NFCI can contribute to foster diversification in banks' income sources (Stiroh (2004)), it can set new risks and challenges for the banking sector (Lepetit et al. (2008)). Very recently, numerous researchers documented that non-interest income and systemic risk are highly positively correlated (Brunnermeier, Dong, and Palia (2020), De Jonghe (2010) and Moore and Zhou (2014), and Bostandzic and Weiss (2018)). From a regulatory and supervisory perspective, quantifying the evolution of these balance sheet items in a stress scenario remains a relevant and unmet need. Modelling non-interest related sources for stress-test purposes is not straight forward as the source of risks and the channel of transmission might differ from the one already investigated in the literature. For instance, trading income is likely to be much more volatile and responsive to

¹Stiroh (2004) shows that the share of non-interest income over net operating revenue (i.e. net interest income plus net non-interest income) increased from 25% in 1984 to 43% in 2001 for US commercial banks. Bank (2000) reports that non-interest income as a percentage of operating income has increased from 32% to 41% for European banks between 1995 and 1998.

²see Figure A.11 in Appendix

³By non-interest income, we mean net non-interest income, which is defined as total non-interest income less total non-interest expense. It refers to brokerage fees, commissions, income from trading activities, securitization, investment banking.

⁴In the US net-interest income is also around 40% (DeYoung and Rice (2004))

financial developments while credit risk is related to slow moving macro variables. NTI is an important element of the Market Risk framework in the EU-wide stress-testing exercise. Every two years the European Banking Authority (EBA) carries out EU-wide stress tests in cooperation with the European Central Bank (ECB), the European Systemic Risk Board (ESRB) and the national supervisory authorities. The sample included in the test covers the largest significant banks supervised directly by the ECB. The exercise uses the EBA's methodology and templates, and the scenarios and key assumptions are developed jointly between the EBA, the ESRB, the ECB and the European Commission. Both aggregate and individual results are published by the EBA. In the current methodology, banks project their trading income for 3 years ahead taking into account the impact of the adverse market risk scenario on their income generating process.⁵

This paper seeks to fill this gap in literature by empirically estimating the linkages between financial risk factors and net trading income. We focus on net trading income as it is the most volatile and therefore the riskiest⁶ of all the non-interest income activities. Our econometric strategy follows a three-step procedure. First we map net trading income as a share of Total Assets (NTI/TA) jointly with bank specific controls and key financial risk factors through the lens of a fixed effects quantile regression model. We estimate the quantile panel model semi-parametrically using the method of moments approach proposed by Machado and Silva (2019). Next, we use this model to derive the empirical conditional cumulative distribution function of NTI/TA. We use the empirical conditional distribution to estimate tail risk measures such as expected capital shortfall and loss probability across banks. Finally, we employ the model to perform a series of multi-step ahead density forecasts.

We use a sample of significant banks under the direct supervision of the Single Supervi-

⁵In the aftermath of the great recession, national authorities have established a series various of stress test exercises to assess the ability of individual financial institutions to absorb losses and maintain sufficient capital levels in adverse economic conditions. In the EU, in line with the Capital Requirements Directive (CRD) and Capital Requirements Regulation (CRR) stress tests were first introduced in 2014 and since then are carried out every two years on a sample covering broadly 70% of the euro area, each non-euro area EU Member State and Norway, as expressed in terms of total consolidated assets. See EBA methodological note (2020)

⁶Given the high volatility, unexpected losses can be generated frequently if appropriate volatility hedging strategies are not in place

sory Mechanism (SSM). Our sample is at a quarterly frequency and spans over the period from the fourth quarter of 2014 up to the first quarter of 2020. We consider risk factors to cover all potential sources of risk for trading income: interest rate risk, credit risk, volatility risk, exchange rate risk, commodity price risk and equity price risk.⁷ We find a strong and asymmetric impact of these risk factors on the tails of the distribution of NTI/TA. In particular, long term interest rate, credit spreads and oil returns exhibit a strong positive effect on the lower quantiles of the NTI/TA distribution that dissipates over higher quantiles. On the other hand, stock returns have a significant (positive) effect only on the right tail of the NTI/TA distribution. By construction all these effects will not be captured in typical OLS panel model. We find that bank-specific characteristics such as the amount of risk-weighted assets and the total equity the banks hold are a poor indicator of NTI/TA performance across quantiles. This finding suggests that banks' individual time-varying characteristics do not matter for trading activities.

Next, based on the proposed model, we perform a series of pseudo stress tests. Based on these hypothetical exercises we show that the volatile nature of trading income can lead to increased downside tail risk, that is, the risk that a bank experiences an extreme trading loss. Extreme returns cause “fatter” tails than a normal distribution would predict. Interlinkages between financial risk factors and trading income indicate that financial crisis and adverse market shocks can produce left tail events which could have a damaging impact on the trading portfolio of banks. We employ the estimated cumulative distribution function to gauge the (time-varying) conditional expected shortfall in terms of capital at different time horizons and across banks. Using expected capital shortfall we can quantify the tail risk as the expected loss conditional on the bank experiencing an extreme event (a loss greater than the 5th or 10th percentile for example). We find that at the onset of the Covid-19 pandemic the expected CET1 ratio⁸ shortfall due to trading income losses at the 5th percentile ranges between -15 and -100 basis points with all banks exceeding what would be considered a material loss. At the 10th percentile, 43 of 54 banks exceed 15 bps of total risk weighted

⁷The risk factors are: the spread between long and short euro area swap rates, the credit spread between BBB corporate bond and euro area swap rate, Brent oil returns, major equity indices returns, the VStoxx index and the return of Euro/US exchange rate.

⁸Common Equity Tier 1 ratio is the ratio of CET1 on risk-weighted assets.

assets. We also compute the probability of each bank exceeding net trading income losses of 15 basis points as a share of risk weighted assets. We find that the median probability at the first quarter of 2020 is above 30% across the sample and ranges between 10% and 60% .

One of the objectives of stress-test models is to forecast of banks' balance-sheet items under different hypothetical stress scenarios. The severity of the stress scenarios is directly related to the realizations of the market risk factors. We use the proposed model to deliver multi-steps forecasts of NTI/TA for banks for various quantiles that is related to the degree in the severity of the scenario.

This paper is related to two main strands of literature. First it relates to the stress-test literature assessing banks resilience to adverse macroeconomic scenarios (e.g. Quagliariello et al. (2004); Coffinet, Lin, and Martin (2009); Lehmann, Manz, et al. (2006); Albertazzi and Gambacorta (2009)). Most of the papers quantify interest income losses in adverse scenarios. One exception is the study by Coffinet, Lin, and Martin (2009) in which they additionally investigate the effect of adverse shocks on other sources of income, such as commissions, fees and trading activities. The drawback of this type of study is that they rely on standard OLS techniques that might fail to capture the potential non-linear effects of risk factors which is a key feature experienced in the data.

Second, we also relate to the literature on the distributional effects of tail shocks. In this respect, many researchers have employed quantile regression techniques. Ghysels, Guérin, and Marcellino (2014) and Schmidt and Zhu (2016) study the distribution of stock returns. Adrian, Boyarchenko, and Giannone (2019) and Figueres and Jarczyński (2020) study the GDP growth of US and Euro Area respectively. Chavleishvili and Manganelli (2019) employ a quantile autoregressive model to examine the effect of tail shocks on Euro area growth rates.

We follow Covas, Rump, and Zakrajšek (2014) and estimate a quantile panel model to examine the non-linear effects of macroeconomic variables to various income components.⁹ Yet, there are at least three main differences between our study and their study. First, they study 15 US public companies while we focus on euro area with a representative sample.

⁹Covas, Rump, and Zakrajšek (2014) use a similar model for US banks.

Secondly, in their study, bank fixed effects are quantile invariant. Instead, in our set up will also allow quantile-variant fixed effects. Thirdly, since we focus on Net Trading Income, we abstract from slow moving macroeconomic variables and instead we use fast moving financial risk factors.

The rest of the paper is organized as follows. Section 2 discusses the data. Section 3 presents the econometric methodology. Section 4 contains the regression results. Section 5 presents our strategy for fitting the conditional distribution. Section 6 deals with the conditional expected shortfall. Section 7 displays the forecasting methodology under adverse stress scenarios. Finally, section 8 concludes.

2 Data and descriptive statistics

This section describes our data set and provides summary statistics related to the asset holdings of European banks, bank characteristics and market risk factors.

2.1 Bank specific variables

The final sample includes 54 of the European banks that participate in the EU-wide stress tests¹⁰ and that are directly supervised by the SSM. We exclude banks to whom the trading exemption was granted (EBA (2018))¹¹. Data are reported at a consolidated level and span over the period that goes from the last quarter of 2014 until the first quarter of 2020.

The sample covers banks from 13 countries of the euro area. The most-represented countries are Germany (10 banks), Spain (11 banks), Italy (7 banks), and France (6 banks). We classify banks as G-SIB and not G-SIB according to the Financial Stability Board (FSB) definition¹². The smallest banks in the sample in terms of total assets held on average 8

¹⁰The EBA has been responsible for stress tests and capitalization exercises that have been conducted in the European banking market since 2010.

¹¹Institutions can request the trading exemption to their competent authorities provided that neither of the following conditions holds:

- The institution has at least one VaR model in place, approved by the competent authority;
- The institution's total market risk capital requirement is greater than 5% of the total capital requirement.

¹²The FSB identifies banks as Globally systemically important banks (G-SIB) using indicators based on size, interconnectedness, financial institution infrastructure, complexity and cross-jurisdictional activity

billions euro of assets while the top banks hold more than 1,000 billions euro of assets. For more detailed description of the sample of banks see Appendix B.

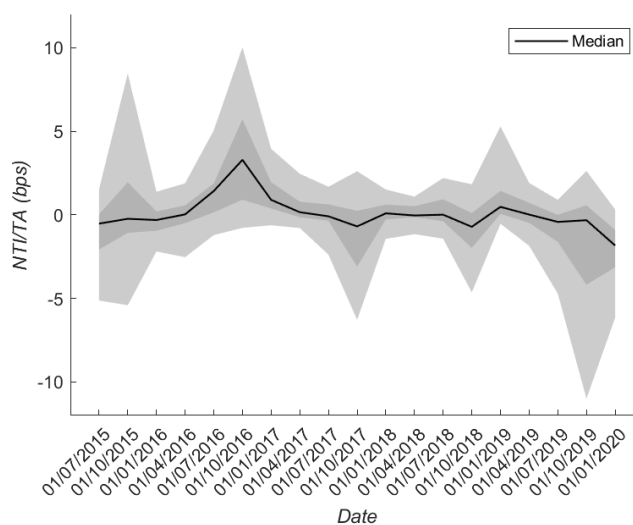
We collect for the 54 banks, risk-weighted assets, total assets, total equity and net trading income¹³. The data source for our bank data is the supervisory regulatory reporting dataset. This is quarterly regulatory data that banks operating in the Euro Zone are required to provide to the competent authority. The data are highly confidential, which is why we abstain from revealing bank-level information.

It is important to recognize several features of the data that might influence the main results. First, some banks have been excluded because of merger and acquisition activity. Second, banks that closed during the sample period were excluded, creating survivorship bias. Third, some of the sample banks trade on a global scale and in multiple financial markets, hence are influenced by international financial conditions. Finally, our time span is relatively short. In order to address these potential concerns we, first, use a model including bank fixed effects. The fixed effects account for time-invariant bank-specific heterogeneity. Second, we complement our baseline specification by an array of robustness checks.

The median (seasonally adjusted) net trading revenue has remain quite stable over time, but there is wide variation among banks. Figure 1 shows the median, 25th and the 75th percentiles of NTI on TA (bps) for the sample of banks under consideration over the period 2015Q2-2020Q1. The median net trading income hovers around 0 bps with a declining trend around the onset of the pandemic but with notable variation across banks.

¹³We follow the provision stated in the EBA methodology (2018) and collected all net trading related revenues defined as in FINREP ('Gains or (-) losses on financial assets and liabilities held for trading and trading financial assets and trading financial liabilities', FINREP 02.00 row 280 and 285..."). Since NTI is reported as the accumulated flow of incomes across quarters over the year, we compute the marginal income flow for each quarter. That is, the flow of NTI in quarter 2 is the reported accumulated NTI in quarter 2 minus the reported NTI in quarter 1 and so on. The data are also seasonally adjusted by regressing on quarterly dummies

Figure 1: NTI over Total Asset (bps). Historical distribution over the sample



Note: Source - ECB supervisory data. The dark grey band identifies the 40th and the 60th percentiles, while the light grey band identifies the 25th and the 75th percentiles.

2.2 Macro-financial risk factors

The set of macro-financial risk factors in our methodology is restricted to those provided in previous EU-wide stress testing scenarios. We select the main risk factors that are linked to various types of financial assets according to the underlying securities. Financial assets are usually broken down in the following risk categories: interest rate products (fixed income securities and interest rate derivatives), credit products such as credit swaps, equity products and commodity related products. Therefore, we select a few risk factors for each category to summarize the possible risk drivers for the different financial assets. To this end, the list of risk factors considered is:

- the spread between the 10 year and 3 month euro area swap rate;
- the spread between the average euro area BBB corporate bonds and 10 year euro area swap rate;
- quarterly equity returns of the major stock index for each member country;

- the quarterly return on the Euro/USD dollar exchange rate;
- the quarterly return on crude Brent oil prices;
- the (logged) 1 month implied volatility index for EuroStoxx 50.

Descriptive statistics are presented in Table 1.

Table 1: Descriptive statistics 2014Q4-2020Q1.

Variables	mean	sd	min	max	obs
NTI/TA	0.01	0.00	-0.01	0.01	1134
RWA/TA	0.41	0.15	0.07	0.92	1134
EQUITY/TA	0.07	0.03	0.02	0.32	1134
Swap Spread	0.91	0.33	0.27	1.30	20
BBB Spread	1.26	0.47	0.62	2.86	20
Oil returns	-0.05	0.23	-0.88	0.15	20
FX returns	0.00	0.04	-0.72	0.08	20
log Vstoxx	2.97	0.35	2.49	3.88	20
Stock index returns					
Austria	-0.01	0.13	-0.46	0.14	20
Belgium	-0.01	0.10	-0.31	0.12	20
Cyprus	-0.02	0.06	-0.12	0.12	20
Germany	-0.01	0.09	-0.29	0.11	20
Spain	-0.02	0.10	-0.34	0.11	20
Finland	-0.01	0.08	-0.23	0.11	20
France	-0.01	0.09	-0.31	0.12	20
Ireland	-0.01	0.11	-0.33	0.14	20
Italy	-0.02	0.11	-0.32	0.16	20
Luxembourg	-0.03	0.13	-0.42	0.12	20
Netherlands	-0.00	0.08	-0.22	0.12	20
Portugal	-0.02	0.08	-0.25	0.10	20
Slovenia	-0.00	0.08	-0.23	0.08	20

Note: Source - ECB supervisory data, Bloomberg and ECB internal databases. Equity and Brent crude oil returns are measured as quarterly percentage change. FX returns are measured as absolute changes in the EURUSD rate. The swap spread and BBB spread are spreads measured in levels. Bank specific variables NTI, RWA and equity are all measured relative to bank total assets also in levels. Note that NTI over TA is converted in basis points when implementing the regression estimation.

3 Empirical Strategy

In this section, we introduce the fixed effects quantile dynamic regression model. We estimate the model semi-parametrically using the method of moments technique proposed by Machado and Silva (2019)¹⁴. We then rely on the former model to compute the expected capital shortfall in section 6 and to generate the n-steps ahead forecasts in section 7. For comparison, we also estimate the standard dynamic fixed effect panel model with ordinary least squares.

3.1 Quantile dynamic fixed effect panel model

Our quantile panel model belongs to the location-scale family models that are expressed as:

$$Y = \alpha + X'\beta + \sigma(\delta + Z'\gamma)U \quad (1)$$

where:

- X is a set of strictly exogenous explanatory variables;
- $(\alpha, \beta', \delta, \gamma')' \in \mathbb{R}^{2(k+1)}$ are the unknown parameters;
- Z is a k -vector of known differentiable (with probability 1) transformations of X with element l given by: $Z_l = Z_l(X), l = 1, \dots, k$;
- $\sigma(\cdot)$ is a known C^2 function such that: $P\{\sigma(\delta + Z'\gamma) > 0\} = 1$;
- U is an unobserved random variable, independent of X , with density function $f_U(\cdot)$ bounded away from 0 and normalized to satisfy the moment conditions

$$E(U) = 0, E(|U|) = 1 \quad (2)$$

¹⁴Quantile panel fixed effects models are notoriously difficult to solve due to the incidental parameter problem. Machado and Silva (2019) proposed one simple method to get around this problem. Alternative computationally intensive techniques are introduced by Koenker (2004), Lamarche (2010), Canay (2011) and Galvao Jr (2011)

The model (1) implies that:

$$Q_Y(\tau|X) = \alpha + X'\beta + \sigma(\delta + Z'\gamma)q(\tau) \quad (3)$$

where $q(\tau) = F_U^{-1}(\tau)$ ¹⁵ and $P(U < q(\tau)) = \tau$. We consider a linear specification where $\sigma(\cdot)$ is the identity function and $Z = X$, therefore we can simplify the quantiles as:

$$Q_Y(\tau|X) = (\alpha + \delta q(\tau)) + X'(\beta + \gamma q(\tau)) \quad (4)$$

where the regression quantile coefficient is:

$$\beta_l(\tau, X) = \beta_l + q(\tau)D_{X_l}^\sigma \quad (5)$$

with $D_{X_l}^\sigma = \frac{\partial \sigma(\delta + Z'\gamma)}{\partial X_l}$.

Using (2) and the exogeneity of the regressors, we can identify the vector of unknown parameters from the following set of moment conditions (we assume i.i.d. data):

$$\begin{aligned} E(RX) &= 0 \\ E(R) &= 0 \\ E[(|R| - \sigma(\delta + Z'\gamma))D_\gamma^\sigma] &= 0 \\ E[(|R| - \sigma(\delta + Z'\gamma))D_\delta^\sigma] &= 0 \\ E[I(R \leq q(\tau)\sigma(\delta + Z'\gamma)) - \tau] &= 0 \end{aligned}$$

where $R = Y - (\alpha + X'\beta) = \sigma(\delta + Z'\gamma)U$, $D_\gamma^\sigma = \frac{\partial \sigma(\delta + Z'\gamma)}{\partial \gamma}$, $D_\delta^\sigma = \frac{\partial \sigma(\delta + Z'\gamma)}{\partial \delta}$

The location-scale model (1) for the sample of European banks ($i = 1, 2, \dots, N$) over

¹⁵We denote with F the cumulative distribution function (CDF).

the sample period (denoted as $t = 1, 2, \dots, T$) can be expressed as:

$$\underbrace{Y_{i,t}}_{\text{NTI/TA}} = \alpha_i + \underbrace{X'_{i,t}}_{\text{Explanatory variables}} \beta + \sigma(\delta_i + X'_{i,t}\gamma)U_{i,t} \quad (6)$$

where:

- $Y_{i,t}$ denotes our variable of interest that is net trading income as a share of the total assets for bank i in period t . It is expressed in basis points;
- $X_{i,t}$ is the matrix of explanatory variables that includes 2 auto-regressive components as trading income streams exhibit time persistence, bank-specific time-varying characteristics such as riskiness of the bank's exposures and risk-factors. For simplicity, we slightly abuse the notation and risk-factors are included in the matrix, even if they are not bank varying, but are country specific¹⁶. The assumptions that the regressors are strictly exogenous and not serially correlated do not hold in this dynamic model. Machado and Silva (2019) claim that the bias on the estimate of the coefficients on the lagged dependent variable is small (Nickell (1981)), and they do not expect it to significantly contaminate the estimate of the other variables of interest. Moreover, we use lagged bank-specific variables in order to reduce potential bias due to endogeneity related to the banks' specific characteristics. As a robustness check we a) use a subset of banks on a longer time horizon to reduce the dynamic bias b) Estimate the regressions using the iterative simulation-based approach proposed by Arellano and Bonhomme (2016) suitable for short panels.

Model (6) implies that:

$$Q_{Y_{i,t}}(\tau|X_{i,t}) = \underbrace{(\alpha_i + \delta_i q(\tau))}_{\substack{\text{quantile-}\tau \text{ fixed effect} \\ \text{for individual } i}} + X'_{i,t}\beta + X'_{i,t}\gamma q(\tau) \quad (7)$$

For model (6), the moment conditions have a convenient triangular structure with respect

¹⁶That is, each bank will have its related risk-factors depending on the country the headquarter resides if the variable is country-specific.

to the model parameters that allows the one-step GMM estimator (Hansen, 1982) to be calculated sequentially:

- Regress $\left(Y_{i,t} - \sum_t \frac{Y_{i,t}}{T}\right)$ on $\left(X_{i,t} - \sum_t \frac{X_{i,t}}{T}\right)$ by OLS to obtain (biased) estimates for $\hat{\beta}$;
- Estimate $\hat{\alpha} = \frac{1}{T} \sum_t \left(Y_{i,t} - X'_{i,t} \hat{\beta}\right)$ and obtain the residuals $\hat{R}_{i,t} = Y_{i,t} - \hat{\alpha}_i - X'_{i,t} \hat{\beta}$
- Regress $\left(|\hat{R}_{i,t}| - \sum_t \frac{|\hat{R}_{i,t}|}{T}\right)$ on $\left(Z_{i,t} - \sum_t \frac{Z_{i,t}}{T}\right)$ by OLS to get $\hat{\gamma}$;
- Estimate $\hat{\delta}_i = \frac{1}{T} \sum_t \left(|\hat{R}_{i,t}| - Z'_{i,t} \hat{\gamma}\right)$;
- Finally use the estimated parameters as starting values and proceed by solving the following linear optimization problem:

$$\arg \min_q \sum_{t=1}^T \sum_{i=1}^N \omega_\tau \rho_\tau \left(\hat{R}_{i,t} - (\hat{\delta}_i + Z'_{i,t} \hat{\gamma}) q \right) \quad (8)$$

where the starting parameter values are replaced by the fitted values of the previous steps. Once again ρ_τ is the standard check function¹⁷ and ω_τ are the weights for each τ . For simplicity we assume equal weights across quantiles.

4 Results

We estimate equation (7) using the method of moments for all quantiles ranging from 10th to 90th percentiles with 10 percentage point increments.¹⁸ We add bank-level fixed effects and we control for time-varying bank characteristics by including the lagged ratio of total equity to total assets and the ratio of risk-weighted assets over total assets. We opted for only two bank specific characteristics to be considered in vector $X_{i,t}$ in order to keep the specifications relatively parsimonious. As it is shown below, the bank specific variables proved to be unimportant determinants of Net Trading income. We also include two lagged

¹⁷ $\rho_\tau(A) = (\tau - 1)I\{A \leq 0\} + \tau I\{A > 0\}$ where the function I is equal to 1 when the condition in brackets is true for a given A .

¹⁸We use a 1000 sample replications bootstrap procedure with replacement to compute the quantile pseudo standard errors and p-values. Note that the bootstrap procedure accounts for heteroskedasticity but not for the presence of serial correlation in the data (no block bootstrap for correlated observations).

NTI/TA values to account for the persistence in the trading activities¹⁹. Lastly, we added an array of exogenous risk factors reflecting macro-financial conditions. We only considered contemporaneous values of the risk factors for two reasons. First, we have a relatively short panel and wanted to keep the specification parsimonious and second we argue that trading income reacts immediately to changes in financial markets.

Table 2 shows the results for the 10th, 30th, 50th, 70th and 90th percentiles together with the OLS estimates (The location and scale parameters are shown in table A.2 in the Appendix). To facilitate interpretation the NTI/TA variable and its lagged values are multiplied by 10000. Starting first with the OLS estimates the entries of table 2 show that the lagged values of net trading income are significant but with alternate signs. The sum of the two coefficients is around 0.2 denote somewhat persistence in net trading income revenues. Positive trading income today (weakly) predicts with positive revenue in the next two quarters. The other two significant financial indicators are the stock returns and the slope of the swap curve both with positive signs. An increase in the slope of the swap curve or higher stock returns reflects on average positive net trading income.

Turning our attention now to the quantile estimates, we first notice that the degree of persistence does not vary markedly across quantiles. Moreover, the sum of autoregressive quantile coefficients is very close to the sum of OLS point estimates. In general this is a very surprising result, indicating that net trading income, does not exhibit local persistence effects. Intuitively, it means that in period of trading losses the series does not become more persistent increasing the left tails of the distribution as in Covas, Rump, and Zakrajšek (2014). Instead, as we see below the exogenous financial variables impact the left tail of the NTI distribution.

The bank-specific indicators controlling for riskiness and capitalization are found to be insignificant across the distribution. Intuitively, the level of risky assets and total equity that a bank holds in its portfolio are not good indicators of its net trading revenues. One possible justification is that banks' fixed effects are sufficient to capture banks' specificities although they are time invariant.

¹⁹The selection of two lags stems from the AIC and BIC information criteria, see Table A.1 in appendix

Table 2: OLS and Quantile Regression estimates for NTI/TA.

NTI/TA $\times 10000$	OLS	Q1	Q3	Q5	Q7	Q9
NTI/TA $_{t-1} \times 10000$	0.41*** (0.06)	0.40*** (0.09)	0.41*** (0.07)	0.41*** (0.06)	0.42*** (0.06)	0.43*** (0.08)
NTI/TA $_{t-2} \times 10000$	-0.21*** (0.03)	-0.17* (0.09)	-0.19*** (0.06)	-0.21*** (0.06)	-0.23*** (0.05)	-0.25*** (0.07)
Equity on Total Assets $_{t-1}$	45.14** (19.72)	54.61 (52.80)	49.01 (41.97)	45.50 (42.70)	41.46 (50.71)	35.55 (69.96)
REA on Total Assets $_{t-1}$	2.58 (7.91)	-5.27 (10.09)	-0.63 (8.16)	2.28 (8.33)	5.63 (9.83)	10.52 (13.51)
Swap Spread 10Y-3M $_t$	2.73** (1.36)	4.47** (1.76)	3.44*** (1.28)	2.80** (1.15)	2.05 (1.25)	0.97 (1.75)
Credit Spread BBB - 10Y $_t$	1.87 (1.28)	6.25** (2.43)	3.66** (1.80)	2.03 (1.64)	0.16 (1.78)	-2.57 (2.46)
Stock returns $_t$	10.73** (4.95)	3.61 (6.06)	7.82* (4.60)	10.46** (4.29)	13.50*** (4.71)	17.94*** (6.37)
Oil returns $_t$	2.52 (1.51)	9.61*** (3.71)	5.42** (2.61)	2.80 (2.16)	-0.23 (2.20)	-4.65 (3.00)
Δ EUR-USD $_t$	-2.12 (6.46)	34.45*** (11.11)	12.84 (8.24)	-0.71 (8.01)	-16.32* (9.30)	-39.13*** (13.58)
EURO VSTOXX $_t$	0.51 (2.01)	-3.52 (2.59)	-1.14 (1.95)	0.36 (1.79)	2.08 (1.95)	4.60* (2.69)
R^2	0.174					
Observations	1026	1026	1026	1026	1026	1026

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The sample period is 2015Q2 up to 2020Q1 and the number of banks equals 54. All specifications include bank fixed effects (not reported). The first column of the table reports coefficients estimated via dynamic fixed effect panel model with OLS estimator. The other columns show estimated coefficients for the 10th to 90th percentiles via the quantile dynamic fixed effect panel model with method of moments estimator. NTI/TA and its lagged values are multiplied by 10000. Equity on Total Assets and REA on Total Assets are lagged. In parenthesis we report bootstrap standard errors (1000 replications) clustered by bank.

On the other hand, macro-financial risk factors have heterogeneous and asymmetric impact across quantiles. Stock returns exert a significant positive effect on higher quantiles whereas the (10Y-3M) interest rate swap spread and the (BBB - 10Y) credit spread on lower quantiles. Oil returns have significant and positive impact on the left tail of the NTI/TA distribution which dissipates over higher quantiles. The EURUSD exchange rate significantly affects the extreme tails of the NTI conditional distribution, negatively on the 90th percentile and positively on the 10th percentile. The importance of interest rate and credit spreads on trading is aligned with the evidence that the large majority of financial instruments in banks' trading portfolio are government and corporate bonds and interest rate related derivative products. These findings can not be visible in the OLS results (refer to the first column)²⁰. Financial conditions captured by granular macro-financial risk factors have an asymmetrical effect on the net trading income conditional distribution. As a robustness check, we re-estimate the model with business model classification fixed effects²¹. The regression results are available in table A.3 in the appendix. Results show that our results are robust and the asymmetrical effect remains.

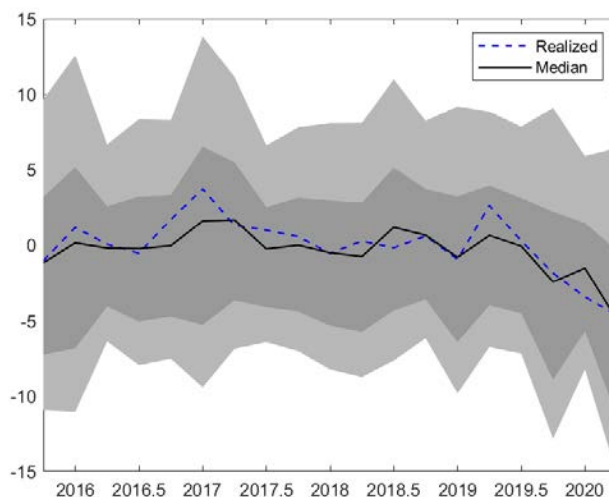
Figure 2 shows the fitted values of the conditional quantiles over time together with the realised values for the aggregate sample of banks²². While median/mean estimates accurately represent the net trading income ratio during normal times, they perform poorly during periods of financial distress. The realised value during the onset of the Covid-19 pandemic markedly deviates from the median and average estimates. However, the realised values lie within the conditional distribution. We also provide Figure A.12 in the appendix which shows the conditional quantiles over time for two individual major banks with significantly different variance.

²⁰These findings complement the existing quantile regression literature using non-linear quantile models. Adrian, Boyarchenko, and Giannone (2019) and Chavleishvili and Manganeli (2019) show that an aggregated financial condition index affects the left side of GDP growth distribution for US and EU respectively but not the right tail.

²¹We control for business model classification as defined by the ECB. Business model classifications categorise banks as G-SIBs, universal banks, investment banks, asset managers, custodian banks and various types of lenders.

²²We aggregate the quantiles to form a combined distribution using a quantile averaging method known as vincentization (see Ratcliff (1979) for further details). Vincentization is a simple method to combine distributions by averaging α per cent quantiles to construct the α per cent quantile of the group where $0 < \alpha < 1$. Therefore, if q_i is the α per cent quantile of F_i , that is $F_i(q_i) = \alpha$ then the predicted distribution would be defined by $F^{-1}(\alpha) = \sum_{i=1}^n w_i q_i$. In our setting all the weights are the same.

Figure 2: Fitted conditional quantile estimates from the quantile dynamic fixed effect panel model.



Note: The panel shows the estimates over the period 2015-2020 at quarterly intervals for the aggregate sample of banks. The aggregate sample distribution is combined using vincentization - a quantile averaging method. The black line is the conditional median quantile, the shaded dark grey defines the 30th to 70th quantiles and the lighter grey the 10th and 90th quantiles. The blue dashed line shows the realised value.

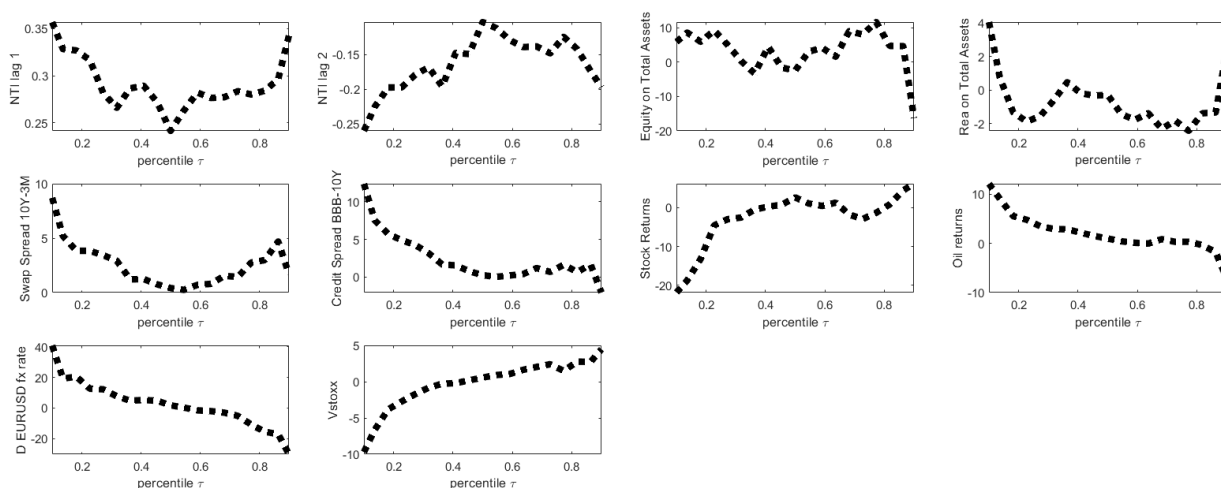
As discussed in section 3, the method of moments approach has the advantage that it is computationally easy to implement, and deals well with the incidental parameter and quantile crossing problem. However, two sources of concern should be investigated. First, the inclusion in the specification of the model of bank-specific variables among the regressors can lead to endogeneity problems. Second, the presence of a auto-regressive regressive component can lead to biased estimates.²³

As robustness check, we consider an alternative method to estimate the dynamic quantile regression. In particular we use the iterative simulation-based approach framework developed by Arellano and Bonhomme (2016) to estimate the model. Under the assumption that $U_{i,t}$ given in equation 6 is independent from the vector $(X_{i,t})$ where $(X_{i,t})$ contains the two

²³The FE-OLS and FE-QAR estimators are biased in the presence of lagged dependent variables as regressors, particularly for panels with a relatively short time series dimension; see for example, Galvao Jr (2011) and (Nickell (1981)). Machado and Silva (2019) show in a simulation exercise that bias arising from the method of moments should be small and not significantly affect the parameter estimates.

lagged values of Y_t and under some starting values for the parameters we can consistently recover the parameters numerically via an extension of the expectations maximization algorithm.²⁴ Following this procedure and setting as starting values the estimates of simple quantile regression we estimate the parameters of equation 6 for quantiles 0.1 up to 0.9 shown in figure 3. The estimates and the paths of all variables with the exemption of equity over total assets are found to be in line with the estimates of the method of moments approach shown in table 2. Overall, we can conclude that the results from the Arellano and Bonhomme (2016) estimation confirm that our main findings are not an artifact of the method of moments regression procedure but reflect a robust property of the conditional distribution of net trading income.

Figure 3: Simulation based quantile Regression estimates for NTI/TA



Note: Parameter estimates from the dynamic quantile model with fixed effects estimated by Arellano and Bonhomme (2016) simulation method. The sample period is 2015Q2 up to 2020Q1 and the number of banks is 54.

As further robustness check, we estimate the model considering other macro-financial controls. In particular, we replace equity returns by Itraxx senior financial returns, Vstocx with VIX and we added as additional regression 10 year sovereign spreads. Table 3 shows that the significance and persistence of net trading income lagged variables hardly change

²⁴For more details on the estimation procedure see Arellano and Bonhomme (2016).

under this different specification. Swap spreads and credit spread parameters are somewhat smaller while the FX parameters are bigger. Finally, consistent with financial indicators the Itraxx senior financials is significant for higher quantiles. The sign is reverted compared to table 2 as higher Itraxx returns reflect worsening financial conditions where for stock returns is the opposite. As final robustness check, we include among the controls a business model of banks and results remain substantially unchanged (see Table A.3).

5 Conditional net trading income distribution

The quantile equation (3) delivers an approximate empirical inverse cumulative distribution function (CDF)²⁵ of the NTI/TA ratio for each quarter and each bank. Mapping the estimates of the quantile function into a probability density function (PDF) is not straightforward because of estimation error and data noise. One way to address this problem is by interpolating the quantile functions using splines and imposing monotonicity and smoothness as in Schmidt and Zhu (2016). Alternatively, as shown by Adrian, Boyarchenko, and Giannone (2019), we can recover the probability density function parametrically by fitting parametric probability function. We therefore smooth the estimated quantile distribution every quarter and for each bank by interpolating between the estimated quantiles using the skewed t-distribution developed by Azzalini and Capitanio (2003). This methodology permits the transformation of the empirical quantile distribution into an estimated conditional distribution.

Following Azzalini and Capitanio (2003) we fit the following probability density function:

$$f_Y(\mu, \sigma, \alpha, \nu) = \frac{2}{\sigma} t\left(\frac{y-\mu}{\sigma}; \nu\right) T\left(\alpha \frac{y-\mu}{\sigma} \sqrt{\frac{\nu+1}{\nu + \left(\frac{y-\mu}{\sigma}\right)^2}}; \nu+1\right) \quad (9)$$

where $t(\cdot)$ and $T(\cdot)$ respectively denote the PDF and CDF of the Student t-distribution. The four parameters of the distribution pin down the location μ , the scale σ , the fatness

²⁵The quantile function of a scalar random variable Y is the inverse of its cumulative distribution function.

Table 3: OLS and Quantile Regression estimates

NTI/TA \times 10000	OLS	Q1	Q3	Q5	Q7	Q9
NTI/TA _{t-1} \times 10000	0.41*** (0.06)	0.41*** (0.09)	0.41*** (0.07)	0.41*** (0.06)	0.40*** (0.06)	0.40*** (0.08)
NTI/TA _{t-2} \times 10000	-0.21*** (0.03)	-0.17* (0.09)	-0.20*** (0.07)	-0.21*** (0.06)	-0.23*** (0.05)	-0.25*** (0.07)
Equity on Total Assets _{t-1}	55.51*** (20.47)	60.87 (54.97)	57.66 (42.83)	55.70 (40.89)	53.52 (45.66)	49.98 (62.24)
REA on Total Assets _{t-1}	3.38 (8.82)	-7.53 (9.84)	-1.00 (8.01)	2.98 (8.26)	7.41 (9.92)	14.61 (13.95)
Swap Spread 10Y-3M _t	2.69* (1.55)	2.40 (1.64)	2.58** (1.26)	2.68** (1.18)	2.80** (1.27)	2.99* (1.71)
Credit Spread (BBB - 10Y) _t	1.55* (0.90)	4.82*** (1.71)	2.86** (1.27)	1.67 (1.17)	0.34 (1.31)	-1.82 (1.85)
Oil returns _t	1.52 (2.03)	7.26* (4.28)	3.82 (3.15)	1.72 (2.72)	-0.61 (2.77)	-4.40 (3.73)
Δ EUR-USD _t	-13.14* (7.44)	24.24* (13.33)	1.86 (10.11)	-11.79 (9.66)	-26.95** (10.62)	-51.63*** (15.08)
US VIX _t	-0.79 (1.54)	-7.94*** (2.53)	-3.66** (1.85)	-1.05 (1.69)	1.85 (1.88)	6.58** (2.62)
Sovereign yield 10Y - 10Y Swap _t	1.48 (1.22)	-0.11 (1.21)	0.84 (1.09)	1.42 (1.28)	2.06 (1.67)	3.11 (2.42)
Itraxx return _t	-3.58* (1.84)	5.93** (2.67)	0.23 (1.99)	-3.24 (1.98)	-7.10*** (2.25)	-13.38*** (3.14)
R^2	0.177					
Observations	1026	1026	1026	1026	1026	1026

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

ν , and the shape α . Relative to the t-distribution, the skewed t-distribution adds the shape parameter which regulates the skewing effect of the CDF on the PDF. Similarly to Adrian, Boyarchenko, and Giannone (2019), we choose the four parameters $\mu_t, \sigma_t, \alpha_t, \nu_t$ every quarter in order to minimize the distance between our estimated quantile function $Q_{Y_t}(\tau|X_t)$ and the quantile function of the skewed t-distribution $F^{-1}(\tau|\mu_t, \sigma_t, \alpha_t, \nu_t)$ to match the 10th to 90th quantiles. Formally, for each bank i :

$$[\hat{\mu}_t, \hat{\sigma}_t, \hat{\alpha}_t, \hat{\nu}_t] = \arg \min_{\mu, \sigma, \alpha, \nu} \sum_{\tau} \left(Q_{Y_t}(\tau|X_t) - F_{Y_t}^{-1}(\tau|\mu_t, \sigma_t, \alpha_t, \nu_t) \right)^2 \quad (10)$$

where $\hat{\mu}_t \in \mathbb{R}, \hat{\sigma}_t \in \mathbb{R}, \hat{\alpha}_t \in \mathbb{R}, \hat{\nu}_t \in \mathbb{R}^+$

Figure 4 shows the smoothed conditional distribution functions $Q_{Y_t}(\tau|X_t)$ for two selected periods: the last quarter of 2019 and the first quarter of 2020. The conditional distribution is very sensitive to changes in financial risk factors. During the onset of the Covid-19 pandemic the tails of the distribution have become fatter, especially the left tails for many of the 54 selected banks. The visible shift to the left and fattening of the tails implies that there is a higher probability of the bank experiencing both negative and extreme NTI losses in following quarter.

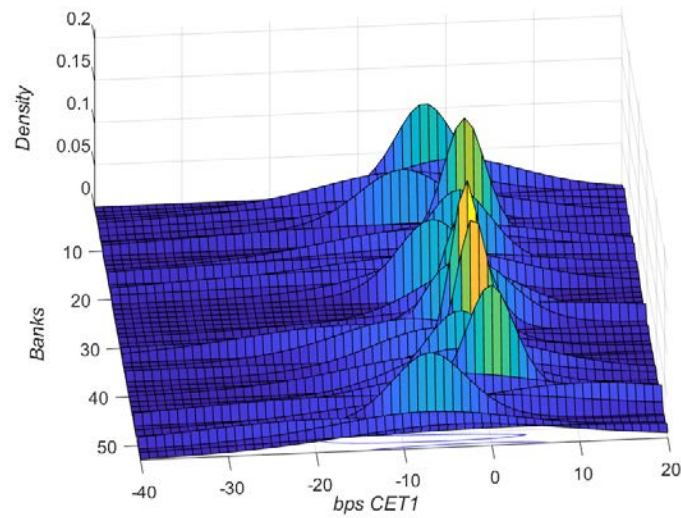
6 Conditional expected shortfall and loss probability

In this section, we estimate expected losses given the sensitivity of a bank to system wide risk factors. The smoothed conditional net trading income distribution is used to estimate two tail risk measures - conditional expected shortfall and the material loss probability. As shown in Adrian, Boyarchenko, and Giannone (2019) we can use the conditional distribution to estimate expected shortfall (ES) and its upper tail equivalent expected longrise (EL). For a given percentile α expected shortfall in the one-step ahead period can be defined as follows

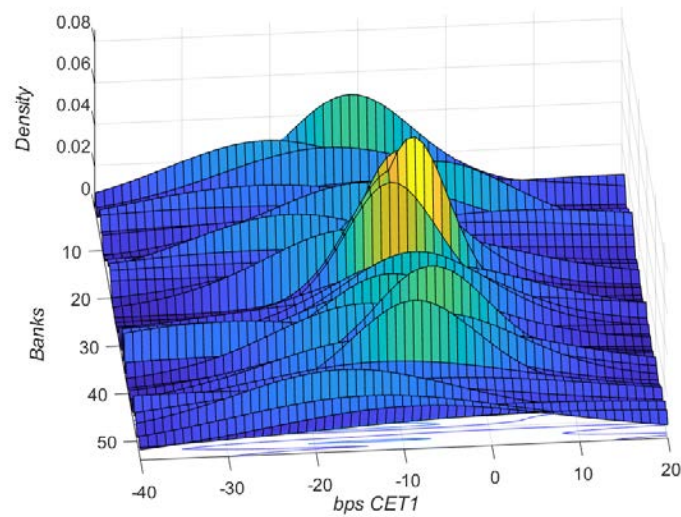
$$ES_{t+1} = \frac{1}{\alpha} \int_0^{\alpha} \hat{F}_{y_t|X_t}^{-1}(\tau|X_t) d\tau \quad (11)$$

where $\hat{F}_{y_t|X_t}^{-1}$ is computed according equation 10.

Figure 4: Conditional NTI/TA distribution.



(a) Conditional distribution Q4 2019



(b) Conditional distribution Q1 2020

Note: The panels show the estimated conditional smoothed distribution of equation (5) for NTI/TA. The top panel shows the conditional distribution in Q4 2019, and the bottom panel in Q1 2020. Each bank in the sample is represented along the z-axis. NTI/TA is presented in basis points.

In the upper tail longrise is defined as

$$LR_{t+1} = \frac{1}{\alpha} \int_{1-\alpha}^1 \hat{F}_{y_t|X_t}^{-1}(\tau|X_t) d\tau \quad (12)$$

The 5% expected shortfall is the conditional expectation of NTI loss, conditional on an NTI loss being below the 5th percentile of the conditional distribution. For the purpose of assessing expected shortfalls and loss probabilities we measure NTI relative to RWAs²⁶ to allow for comparison to CET1 ratios.²⁷ We define an NTI loss greater than 15bps of total RWAs as material. Since expected shortfall (longrise) is an average over all losses in the tail that exceed a value at risk defined at α percentile of the conditional distribution it is very sensitive to NTI losses (profits) deep in the tail. This makes an appealing tail risk measure as it can capture fat tails which are characteristically present in financial distributions such as NTI.

To estimate the material loss probability (MLP) we ask what is the probability that a loss is material in the next quarter (exceeds 15bps of total RWAs):

$$MLP_{t+1} = \int_0^{0.0015} \hat{F}_{y_t|X_t}(\tau|X_t) d\tau \quad (13)$$

where $\hat{F}_{y_t|X_t}$ is the CDF of the fitted skewed t-distribution estimated according to equation 10.

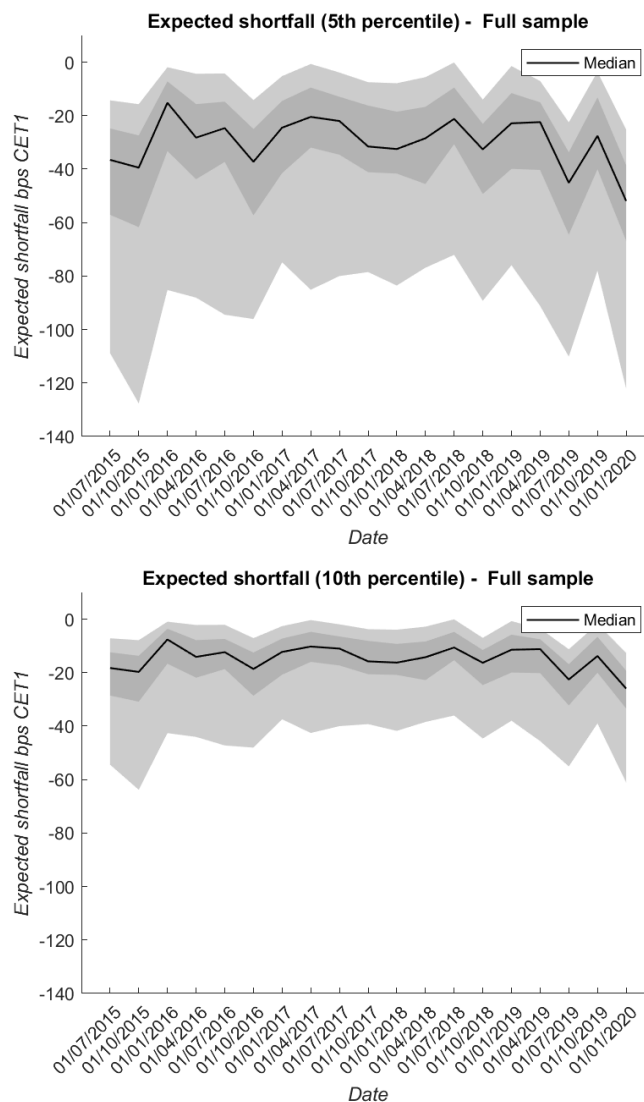
Figure 5 shows the conditional expected shortfall at 5 and 10 percent levels for the full sample of banks. The conditional distribution changes over time and is extremely sensitive to shocks in financial risk factors. Based on the estimated model the Covid-19 crisis leads to a marked increase in expected CET1 loss at both 5 and 10 percent in the first quarter of 2020. In the 5 percent tail there is wide variation across banks as shown in Figure 5 expected losses vary from 20bps to 120bps for banks at the extremes, evidence of fat tails shown in the conditional NTI distribution. At the height of the Covid-19 crisis all 54 banks

²⁶In order to derive this ratio, we multiplied NTI by TA and divided it by RWA.

²⁷The standard regulatory benchmark for measuring bank solvency is the common equity tier 1 (CET1) ratio, measured as common equity capital relative to risk weighted assets (RWAs). Under European capital requirement regulation (CRR) banks are required to hold a minimum amount of regulatory capital to ensure they can withstand stress. CET1 capital is the highest quality capital that a bank holds and will be the first to absorb losses.

have a 5% expected capital shortfall greater than a material loss of 15bps RWAs, and 43 banks have a 10% expected shortfall greater than 15bps RWAs. This means that if a bank experiences a tail loss the expectation is that it will be material.

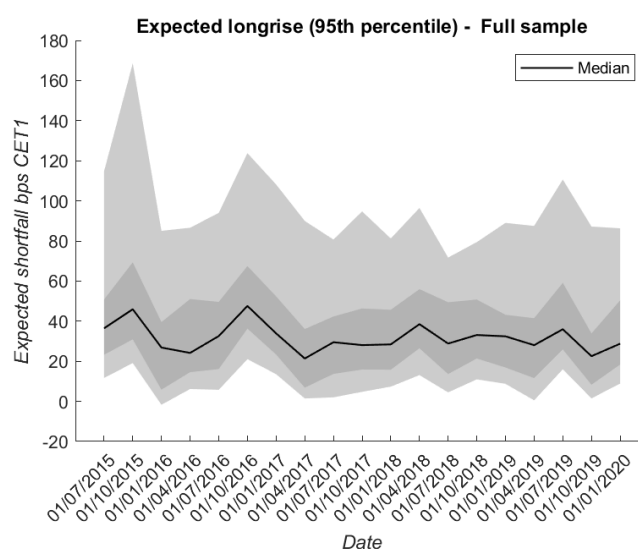
Figure 5: Conditional expected capital shortfall.



Note: The graph shows expected shortfall for banks over the sample period 2015 - 2020 Q1 as defined in equation (11). The upper panel shows the 5% expected shortfall and the lower panel shows the 10%. Each quarterly observation on the graph shows the cross sectional distribution across the sample of banks. The black line represents the bank with the median expected shortfall, the shaded dark grey defines the banks at the 30th to 70th quantiles and the lighter grey the 10th and 90th quantiles. Expected shortfall is expressed in basis points of NTI/RWA.

For most banks in the sample the extreme left tail quantile is more sensitive to risk factor shocks than less extreme quantiles. Figure 6 shows the upper tail of the conditional distribution and measures the expected growth in NTI conditional that the growth is above the 95th percentile. The upper tail of the conditional NTI distribution is also highly sensitive to changes in financial conditions. We find that both right and left tails of the conditional NTI distribution to be sensitive to changes in financial conditions.²⁸

Figure 6: Conditional expected capital longrise.

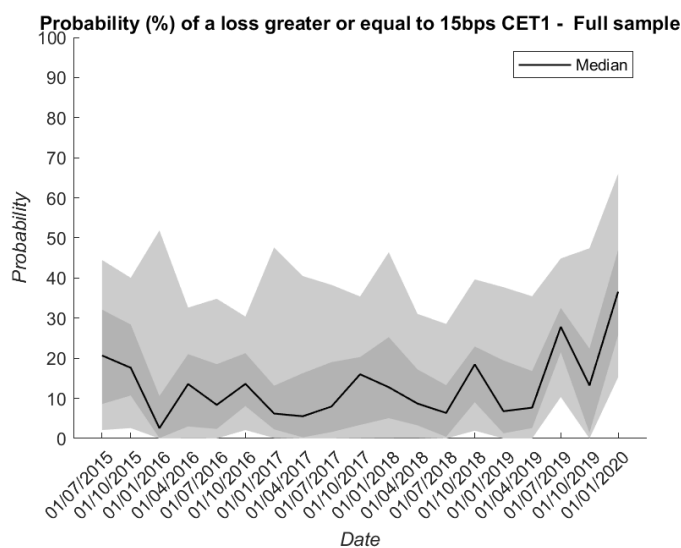


Note: The graph shows the conditional expected capital growth conditional on NTI/RWA being above the 95th percentile as defined in equation (12). Each quarterly observation on the graph shows the cross sectional distribution across the sample of banks. The black line represents the bank with the median expected longrise, the shaded dark grey defines the banks at the 30th to 70th quantiles and the lighter grey the 10th and 90th quantiles. Expected longrise is expressed in basis points of NTI/RWA.

Figure 7 shows the probability of a material NTI loss occurring in the following quarter. The chart illustrates the increase in probability in the first quarter of 2020 with the median probability of experiencing a an NTI loss greater than 15bps total RWAs in Q2 2020 is 37 percent.

²⁸Unlike Adrian, Boyarchenko, and Giannone (2019) who find that the left tail of the GDP growth to be sensitive to financial conditions and the right tail stable over time.

Figure 7: material loss probability.



Note: The graph shows the short term probability of a loss being equal to or exceeding 15bps in the following quarter as defined in equation (13). Each quarterly observation on the graph shows the cross sectional distribution across the sample of banks. The black line represents the bank with the median probability of exceeding 15bps, the shaded dark grey defines the banks at the 30th to 70th quantiles and the lighter grey the 10th and 90th quantiles.

7 Forecasting stress net trading income and the expected shortfall

We can use the model to generate forecasts n -periods ahead conditional on different stress scenarios. Given the non-recursive specification of our setting we must specify the dynamics of the exogenous parameters. We adopt a simple approach and we assume that each exogenous variable follows a quantile autoregressive process²⁹. Then, we iterate forward the Q-AR(1) process to derive density forecasts for each variable. In a second step we lag the forecast and we iterate forward to generate n -steps ahead density forecasts for the NTI³⁰. We adopt two different approaches in order to project reasonable NTI values. First, we assume

²⁹Variables with a panel dimension follow a panel quantile process (i.e. as for country-level equity indices)

³⁰A potential problem with this approach is that the predicted density often exhibits, in finite samples, “quantile crossing” — that is, the predicted conditional quantile function is not monotonically increasing in q . A potential solution is developed by Chernozhukov, Fernández-Val, and Galichon (2010) that suggest the rearrangement of the predicted quantile function to make it monotone. This alternative was ensuring monotonicity, but the forecast NTI was experiencing extreme behaviour in the tails of the distribution when coupling tail estimates with tail realization of the explanatory variables.

that a static-balance sheet assumption holds as it is customary in the EU-wide Stress Test Exercise. That is, bank-level explanatory variables stay constant over the forecast horizon. Second, we project the quantile realizations of NTI using the the median realization of the risk factors.

Risk-factors follow therefore this process:

$$Q_X(\tau|X_{t-1}) = v(q) + m(q)X_{t-1} + u_t \quad (14)$$

While bank-level variables evolve, for each quantile, as follow:

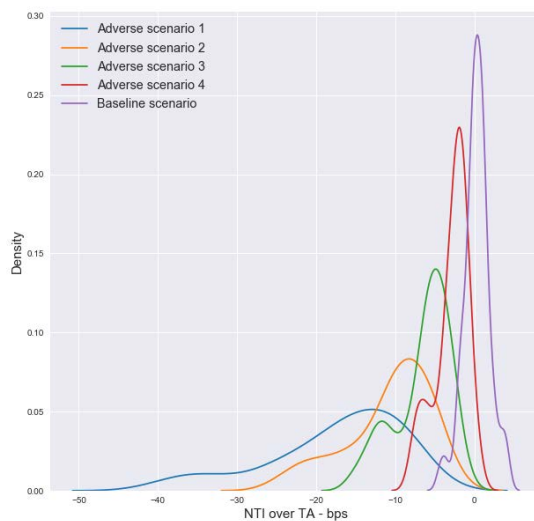
$$X_{t+1} = X_t \quad (15)$$

For n-step ahead forecasts we iterate equations (14) and (15) recursively for each quantile and we plug the median density forecast into the fitted equation (7).

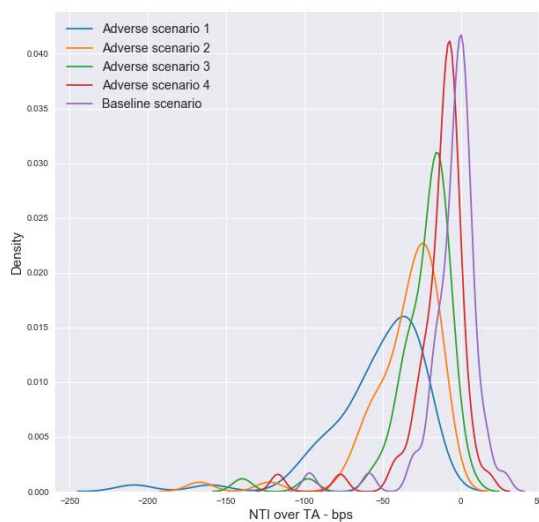
Table 4 shows descriptive statistics for the conditional forecast quantiles. We report statistics for NTI/TA for 4 stress scenarios and the baseline scenario one year ahead (Q4 2020). We define the baseline scenario as the median NTI forecast for each bank. The four adverse scenarios are defined as the conditional forecast at 10th, 20th, 30th and 40th percentiles of the NTI over total assets in order to capture higher degree of severity.

We can visualise the conditional NTI forecasts in Q4 2020 using a kernel density estimation in figure 8a. The wide dispersion of losses and long left tail is especially clear in the most severe scenarios. We see a similar picture when we aggregate losses over each of the quarters of 2020 as shown in figure 8b. The joint distribution of the conditional NTI forecast in the baseline and adverse 4 scenario is shown in figure 9.

Figure 8: Conditional forecast distributions.



(a) Forecast conditional distributions of NTI/TA (bps) across banks in 2020 Q4. The different distributions correspond to different stress scenarios where Adverse scenario 1 is the 10th percentile of NTI/TA.

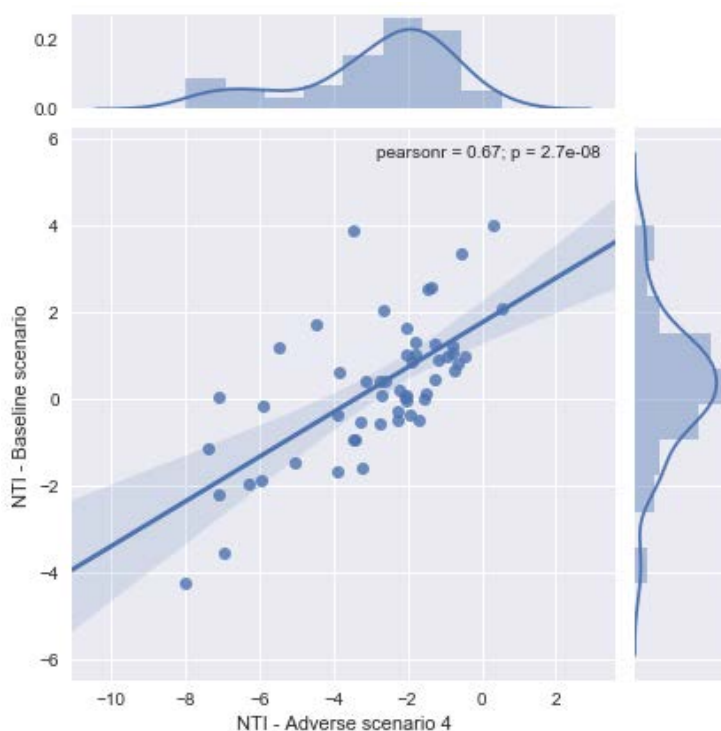


(b) Forecast conditional distributions of NTI/TA (bps) across banks cumulative over 2020. The different distributions correspond to different stress scenarios where Adverse scenario 1 is the 10th percentile of NTI/TA.

Table 4: Descriptive statistics NTI/TA forecast under stress scenarios at Q4 2020

	mean	sd	min	max	kurtosis	skewness
Adverse 1	-17.47	8.49	-39.70	-6.97	3.18	-0.99
Adverse 2	-10.84	5.35	-24.76	-3.63	2.99	-0.95
Adverse 3	-6.51	3.43	-15.10	-1.40	2.80	-0.90
Adverse 4	-2.86	2.08	-7.98	0.53	2.96	-0.87
Baseline	0.29	1.60	-4.24	4.01	3.84	-0.19
Observations	54					

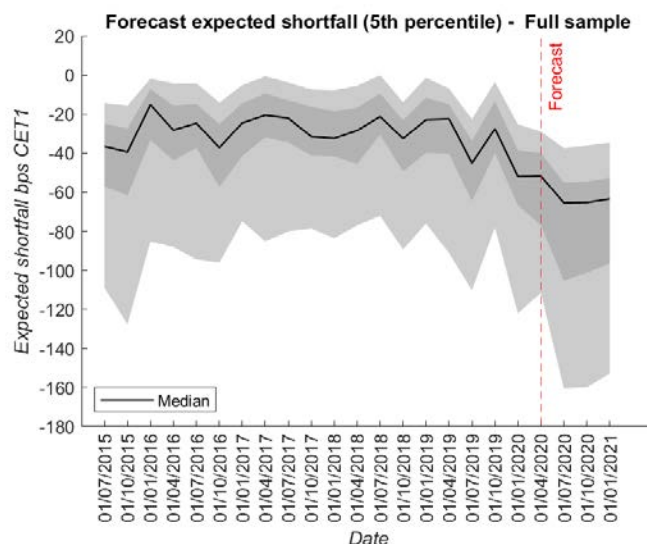
Figure 9: The graph shows the joint distribution of NTI/TA (bps) in 2020Q4 for Baseline and Adverse scenario 4. Each point represents a bank.



Using the conditional quantile forecasts, we follow the same methodology as described in Section 6 and estimate the conditional NTI distribution for the following 4 quarters. From this we estimate the tail risk measures and forecast expected losses across banks. Figure 10 shows the forecast 5 percent expected shortfall from Q2 2020 to Q1 2021. After the onset of the Covid-19 crisis the forecast shows a median decrease of 10bps CET1 ratio over the

4 quarters (expected NTI loss increases from 52bps to 63bps). The heterogeneity across banks also increases, as shown in Figure 10 expected NTI losses vary from 35bps to 153bps CET1 ratio in Q1 2021.

Figure 10: Forecast capital expected shortfall.



Note: The graph shows the expected 5th percentile expected shortfall including the forecast 4 quarters ahead (Q2 2020 - Q1 2021). Each quarterly observation on the graph shows the cross sectional distribution across the sample of banks. The black line represents the bank with the median expected shortfall, the shaded dark grey defines the banks at the 30th to 70th quantiles and the lighter grey the 10th and 90th quantiles. Expected shortfall is expressed in basis points of NTI/RWA.

8 Conclusion

We show empirically the heterogeneous and asymmetric impact of financial risk factors on the distribution of NTI/TA across a large sample European Banks. We estimate via the method of moments (Machado and Silva (2019)) a dynamic fixed effects quantile model and we demonstrate how it can be used to derive plausible measures and probabilities of a capital shortfall for stress test participating banks.

The model can be used for stress test exercises. The values of financial risk factors are available in real time from various market providers. Using the model (quantile), it

is possible to make projections the NTI taking into account the possible development of macro-financial variables and banks' characteristics.

Our methodology could be also employed and extended in other non-interest income sources such as commission fees and operation income. The key risk factors are likely to differ, but distributional effects should also be substantial. With the exemption of Coffinet, Lin, and Martin (2009) and Kok, Mirza, and Pancaro (2019) the literature on other sources of income is scarce.

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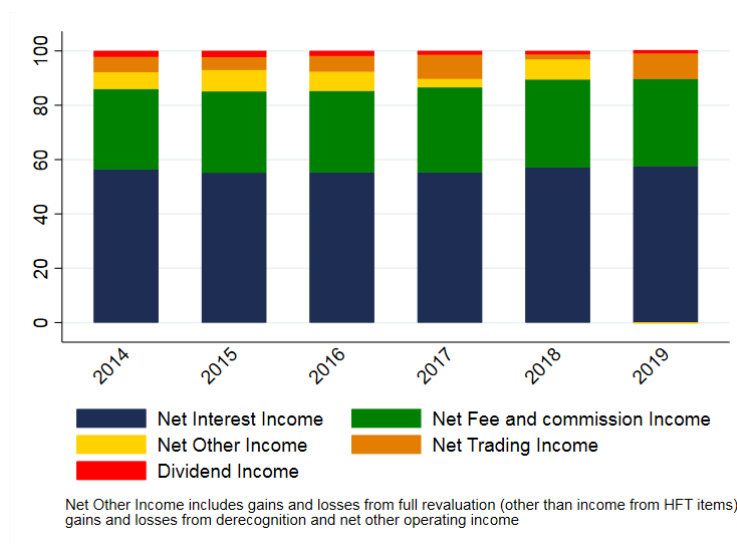
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Appendix A Additional Figures and Tables

This section presents additional table and figures described and cited in the main text.

Figure A.11: Share of Net operating Income Components



Source: Finrep Supervisory Data. Data refer to the aggregated sample of selected banks.

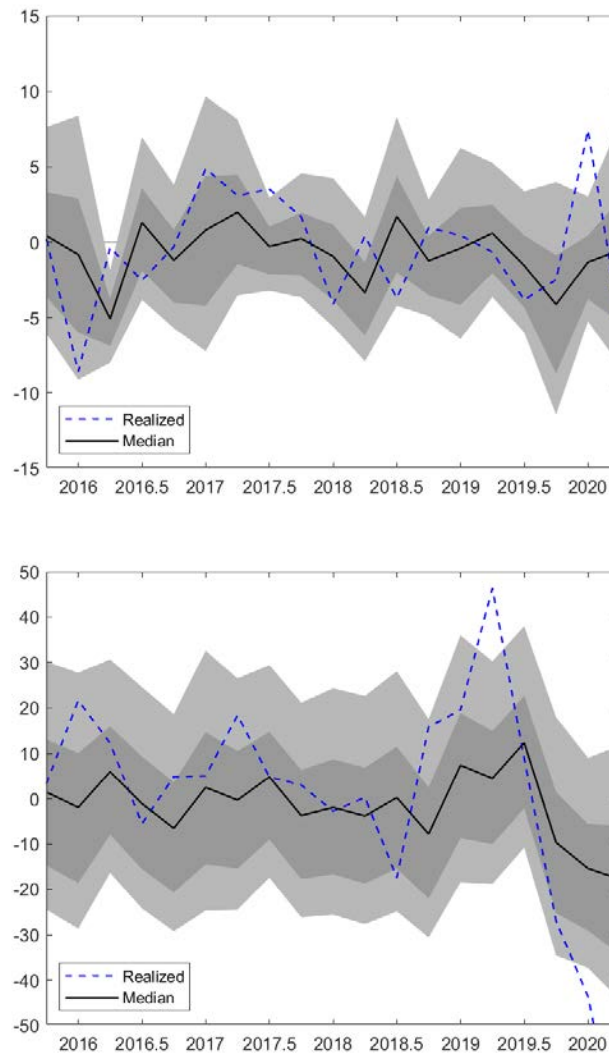
Table A.1: Information criteria for model selection

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
no AR component	1,080	-3899.922	-3886.471	8	7788.943	7828.82
1 AR component	1,080	-3899.922	-3830.181	9	7678.362	7723.225
2 AR components	1,026	-3714.13	-3615.839	10	7251.678	7301.012

Table A.2: Location and scale parameters

Parameters	l_{nti}	$l2_{nti}$	l_{EQ_TA}	l_{REA_TA}	EUR_SWAP_spread
Location	.4126431	-.2106795	45.13509	2.580486	2.728352
Scale	.0094307	-.0232075	-5.552004	4.599206	-1.0196
Parameters	BBB_spread	ESX_gr	OilP	DFX	V2X
Location	1.866115	10.72951	2.523147	-2.117668	.5145152
Scale	-2.569347	4.173657	-4.153611	-21.43572	2.367466

Figure A.12: Fitted conditional quantile estimates from the quantile dynamic fixed effect panel model.



Note: Each panel shows the estimates for a major bank over the period 2015-2020 at quarterly intervals. The black line is the conditional median quantile, the shaded dark grey defines the 30th to 70th quantiles and the lighter grey the 10th and 90th quantiles. The blue dashed line shows the realised value.

Table A.3: OLS and Quantile Regression estimates with Business Model Fixed-effects

	OLS	Q1	Q3	Q5	Q7	Q9
NTI Lag 1	0.41*** (0.06)	0.40*** (0.09)	0.41*** (0.06)	0.41*** (0.06)	0.42*** (0.06)	0.43*** (0.08)
NTI Lag 2	-0.21*** (0.03)	-0.20** (0.08)	-0.21*** (0.06)	-0.21*** (0.05)	-0.22*** (0.05)	-0.23*** (0.07)
Equity on Total Assets	45.14** (19.72)	52.43* (29.44)	27.87 (21.90)	16.83 (23.59)	5.15 (28.50)	-20.16 (45.17)
REA on Total Assets	2.58 (7.91)	-8.81* (5.33)	-3.52 (3.96)	-1.15 (4.13)	1.37 (4.84)	6.82 (7.57)
Swap Spread 10Y-3M	2.73** (1.36)	4.36** (1.77)	3.31*** (1.20)	2.84*** (1.10)	2.34** (1.15)	1.26 (1.72)
Spread (BBB - 10Y)	1.87 (1.28)	6.03** (2.37)	3.20* (1.69)	1.93 (1.59)	0.58 (1.69)	-2.34 (2.44)
Stock indices - P-change	10.73** (4.95)	2.34 (6.16)	7.81* (4.37)	10.28** (4.16)	12.88*** (4.43)	18.52*** (6.29)
Oil Price - P-change	2.52 (1.51)	9.67*** (3.62)	4.87** (2.41)	2.71 (2.07)	0.43 (2.04)	-4.51 (2.91)
D EURUSD fx rate	-2.12 (6.46)	31.96*** (11.27)	8.78 (7.87)	-1.62 (7.92)	-12.65 (8.93)	-36.52*** (13.71)
EURO VSTOXX	0.51 (2.01)	-3.45 (2.47)	-0.76 (1.78)	0.45 (1.70)	1.73 (1.82)	4.51* (2.61)
R^2	0.174					
Observations	1026	1026	1026	1026	1026	1026

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The first columns of the table reports coefficients estimated via dynamic fixed effect panel model with OLS estimator. The other columns show estimated coefficients for the 10th to 90th percentiles via the quantile dynamic fixed effect panel model with method of moments estimator. Equity on Total Assets and REA on Total Assets are lagged.

Appendix B Sample Selection

We aim to construct a relatively homogeneous sample in terms of size and geography. We start with all significant institutions at the highest level of consolidation within the Single Supervisory Mechanism (SSM). To limit the impact of bank exits or entries in the sample, we drop banks that were not present in all years of the period we consider (2014-2020). We also drop banks with trading exemption activities and banks which many zero entries on their total trading portfolio over the sample period.

In our sample, we consider banks considered small, medium, and big based on the number of total assets held in their portfolios as at the end of 2020. To this end, our final sample covers 54 banks from 13 European countries. 8 out of 54 banks are classified as G-SIBs by the Financial Stability Board (FSB) as of November 2020. The table B.4 shows the distribution of our sample banks by country, size and the coverage of the banking system's total assets.

Table B.4: Distribution of the sample banks

Country	G-SIB Banks	Banks	Total Assets G-SIB (Mn)	Share of Total Assets (%)
Austria	0	5		2.64
Belgium	0	5		2.60
Cyprus	0	1		0.08
Germany	1	9	1,490	17.85
Spain	1	10	1,524	15.99
Finland	0	1		0.65
France	4	6	6,830	40.09
Ireland	0	1		0.31
Italy	1	7	873	9.69
Luxembourg	0	3		0.33
Netherlands	1	3	944	8.84
Portugal	0	2		0.85
Slovenia	0	1		0.07
Total	8	54	11,661	100

Note: Source - ECB supervisory data. G-SIB banks refers to the globally systemic bank published in the financial stability report as of November 2020. Banks are the number of sample banks. Total assets G-SIB indicates the Total assets measured in million of euros hold by the G-SIB banks in the country. Share of total assets is the percentage of total assets the banks of the country hold in their balance sheets relative to the overall sample

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