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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 revenue for many euro area banks deemed to be highly sensitive to changes in financial market conditions. We propose a two-step econometric approach to quantify the downside risk of financial shocks on the banks' trading revenues. First, we estimate the parameters of a fixed-effects quantile autoregressive model conditional on exogenous macro-financial shocks and bank characteristics. In the second step, we approximate the entire empirical conditional distribution of net trading income across all banks and time horizons by interpolating between the estimated quantiles. Based on the estimated distribution function, we derive two key metrics that summarize conditional left tail risks: i) conditional shortfall, ii) material loss probability. These measures are relevant in a stress test exercise whose aim to gauge CET-1 capital depletion under an adverse macro-financial scenario. We apply our methodology on supervisory data for a representative sample of European banks over the period spanning from the first quarter of 2015 to the last quarter of 2020. We find that the lower quantiles of net trading revenue distribution are significantly impacted by deteriorating financial conditions, whereas the upper quantiles seem to be stable over time.

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

JEL Codes: C21, C23, G21, G28

Non-Technical Summary

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 sources of risks for the banking sector.

From a regulatory and supervisory perspective, quantifying and modeling these balance sheet items' evolution in a stress scenario remains a relevant and unmet need. Modeling 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 empirically estimate the link 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, financial variables have a robust effect on the lower quantiles of the NTI/TA distribution, an effect that dissipates over higher quantiles. Moreover, the right tail of the conditional distribution is found to be unresponsive to extreme events. Both the quantile regression estimates and the conditional expected shortfall measure corroborate this finding. These asymmetries on the evolution of conditional net trading income distribution indicate that extreme financial returns cause "fatter" left-skewed conditional net trading revenue distributions that could have a damaging impact on the trading portfolio of banks.

One of the objectives of stress-test models is to forecast 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. In this this respect, the model can be used to deliver conditional expected shortfalls of NTI/TA for banks for various quantiles that reflect different degrees in the severity of the scenario.

1 Introduction

Traditionally, banks intermediate funds between depositors and borrowers collecting interest rate margins. However, market deregulation and the protracted low-interest rates have fostered banks diversifying away from interest-related source of income.[1] Recently, a large fraction of banks' revenue arises from customer service fees (i.e. overdraft fees or service loans fees) and trading financial assets. In the euro area, around 40% of banks' overall net operating income arises from non-interest income activities with net fee and commission income (NFCI) and net trading income (NTI) to be the most important contributors.[2]

The rising contribution of non-interest income to the banks' profitability is associated with emerging risks to the banking sector. Non-interest income, especially its sub-component net trading income, is more volatile than interest income and adversely linked to stock market risk conditions (Williams (2016)). To assess these risks, regulators often rely on standard linear panel econometric models. Nonetheless, such models by construction fail to adequately capture the impact of financial shocks at the extremes of the non-interest income distribution. For instance, Covas, Rump, and Zakrajšek (2014) show that a quantile panel model has a superior performance capturing capital shortfalls during cyclical downturns than a standard fixed effects panel model.

In this paper, we propose a novel approach to model empirically the entire distribution of NTI as a function of bank-specific characteristics and key financial risk factors.[3] We estimate the conditional distribution of NTI using a fixed effect quantile autoregressive model. Differently from Covas, Rump, and Zakrajšek (2014), we allow for bank fixed effects to be quantile varying. This additional source of heterogeneity proves to be relevant in modeling the NTI's distribution. We estimate the model semiparametrically using the method of moments technique suggested by Machado and Silva (2019). Next, we use the empirical conditional distribution to compute two key metrics that summarize conditional left tail risks: a) conditional expected shortfall and b) the conditional probability for material loss.[4] Conditional expected shortfall mea-

[1]Stiroh (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. European Central 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.

[2]Net non-interest income 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.

[3]We opted to model the net trading income, rather than net fee and commission income, as is the riskier component of non-interest income. Modeling other interest and non-interest income components is a promising research area that we plan to pursue in the future.

[4]We interpolate across quantiles to derive the entire empirical conditional cumulative distribution function of NTI/TA.

sures the capital shortfall that arises from trading activities at the left of the conditional distribution, such as the 5th or 10th percentile. On the other hand, material loss probability gauges the bank's likelihood of reaching a certain capital depletion threshold.

We apply our methodology to supervisory data for a representative sample of 54 European significant banks under the direct supervision of the Single Supervisory Mechanism (SSM) in the period 2015Q1-2020Q4. Our main findings are that the financial risk factors have a robust impact on the left tail of the distribution of NTI/TA, while the effects appear to be small and insignificant on the right tail. In other words, we find 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. Nonetheless, the right tail of the conditional distribution is found to be unresponsive to extreme events. Both the quantile regression estimates and the conditional expected shortfall measure corroborate this finding. These asymmetries on the evolution of conditional net trading income distribution indicate that extreme financial returns cause "fatter" left-skewed conditional net trading revenue distributions that could have a damaging impact on the trading portfolio of banks.

We complement our baseline estimates with a battery of robustness checks. First, we extend the set of control variables likely to affect net trading income and we find that financial variables significantly affect the left side of the conditional net trading income distribution.[5] We estimate the model restricting the sample to the pre-Covid-19 period, the effect on the left of the distribution dissipates.

Finally, we formally examine the hypothesis that all the 54 bank-specific fixed effects are quantile invariant, as in Covas, Rump, and Zakrajšek (2014). This hypothesis is rejected at the 0.1% significance level. In economic terms, the banks in our sample seem to behave differently under scenarios of varying severity and the generalization of the model of Covas, Rump, and Zakrajšek (2014) allows us to capture this aspect that proves to be statistically relevant.

Our modeling framework could be used for supervisory purposes, e.g., for stress test exercises where the aim is to quantify the tail losses of the banks in a highly adverse macroeconomic scenario. Modeling net trading income for stress-test purposes is not straightforward as the source of risks and the transmission channel might differ from the one already investigated in the literature. For instance, as we show in this paper, trading income is much more volatile and responsive to financial developments, while interest-related risk reactions are found to respond primarily to slow-moving macro variables (Albertazzi and Gambacorta (2009)).

[5] We include additional macro-financial variables such as VIX volatility index, quarterly returns on the European Itraxx index and 10-year country-specific sovereign spreads

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., Acharya, Engle, and Richardson (2012); Covas, Rump, and Zakrajšek (2014); Acharya, Engle, and Pierret (2014); Coffinet, Lin, and Martin (2009); Lehmann, Manz, et al. (2006); Albertazzi and Gambacorta (2009); Schuermann (2014); Quagliariello et al. (2004)). 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 main 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 Jarociński (2020) study the GDP growth of the 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.

More closely related to us is the study by Covas, Rump, and Zakrajšek (2014). They also use a fixed-effects quantile autoregressive model in a stress test environment. Yet, to keep their model computationally tractable, they restrict the fixed effects to be quantile invariant. Using our sample of 54 banks, we test formally via an F-test this assumption.[6] Our paper uses a computational technique that allows the bank fixed effects to affect the entire distribution rather than to act only as a location shifter.

Moreover, we move beyond the discrete quantile estimates and transform the cumulative distribution function from the quantile regression into a density function as in Adrian, Boyarchenko, and Giannone (2019). The procedure is computationally straightforward and permits to compute of tail measures at the extreme of the distribution.

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. Sensitivity checks are conducted in section 5. Section 6 presents our strategy for fitting the conditional distribution. Section 7 deals with the conditional expected shortfall and material loss probability metrics. Finally, section 8 concludes.

[6]We thank Joao Santos Silva for suggesting how to test this hypothesis

2 Data and descriptive statistics

The source for bank-level data is the supervisory regulatory reporting dataset (SUBA). This is quarterly regulatory data that banks operating in the Euro Area are required to provide to the competent authority. We collect, for each bank, risk-weighted assets, total assets, total equity and net trading income.[7] All the data are reported at a consolidated level and span over the period that goes from the first quarter of 2015 until the last quarter of 2020. In the SUBA dataset, 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 highly confidential, which is why we abstain from revealing bank-level information.

The sample includes 54 European banks across 13 countries that regularly participate in the EU-wide stress tests and that are directly supervised by the Single Supervisory Mechanism (SSM).[8] We classify banks as G-SIB and not G-SIB according to the Financial Stability Board (FSB) definition.[9] The smallest banks in the sample in terms of total assets held on average 8 billion euros of assets, while the top banks hold more than 1,000 billion euros of assets. For a more detailed description of the sample of banks, see Appendix B.

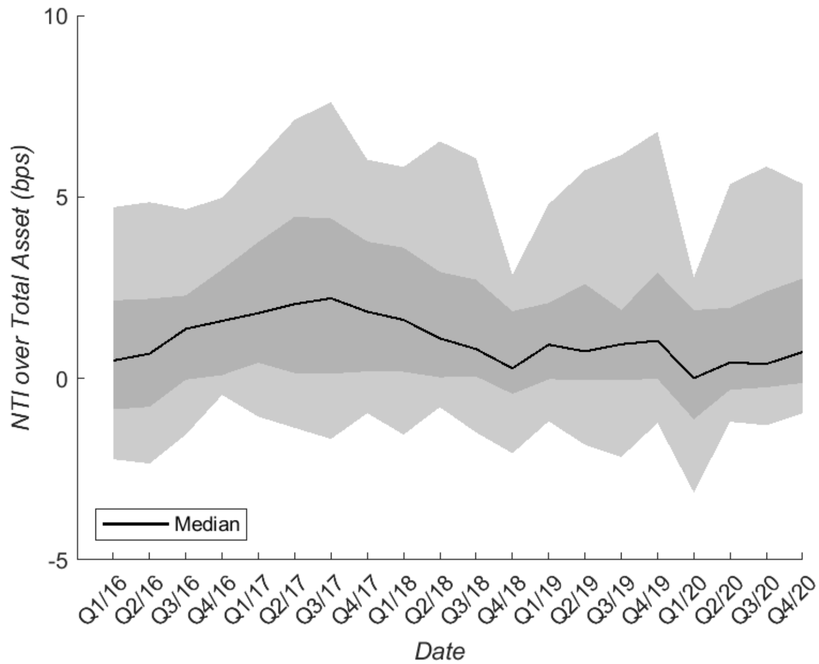
Figure 1 shows the 4 quarter moving average of the median, 25th and the 75th percentiles of NTI on TA (bps) for the sample of banks over the period 2016Q1-2020Q4. Despite the fact that for the median bank the net trading revenue has remained quite stable over time i.e. hovers slightly above 0, there is considerable variation among banks. Standard OLS regressions that center around the mean estimates often fail to capture these developments.

[7]We follow the provision stated in the EBA methodology (2018) and collect 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...").

[8]The most-represented countries are Germany (10 banks), Spain (11 banks), Italy (7 banks), and France (6 banks).

[9]The FSB identifies banks as Globally Systemically Important Banks (G-SIB) using indicators based on size, interconnectedness, financial institution infrastructure, complexity and cross-jurisdictional activity

Figure 1: Historical distribution of NTI/TA over the sample



Note: Source - ECB supervisory data. The chart shows the evolution of the 4 quarters moving average of NTI/TA for the period 2016Q1 up to 2020Q4. The dark gray band identifies the 40th and the 60th percentiles, while the light gray band identifies the 25th and the 75th percentiles.

The set of macro-financial risk factors in our methodology is restricted to those provided in previous EU-wide stress testing scenarios and 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 into the following risk categories: interest rate (fixed income securities and interest rate derivatives), credit e.g. credit swaps, equity, FX 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. In the core sample, the set of risk factors are:

- 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 (log) 1-month implied volatility index for EuroStoxx 50.

Moreover, we consider an additional set of risk factors in the sensitivity analysis in section 5:

- the spread between the 10-year sovereign bonds by country of origin and 10-year euro area swap rate;
- The 5Y euro area quarterly itraxx financial returns ;
- the (logged) 1-month implied volatility index for US index S&P 500.

The descriptive statistics of all the variables are presented in Table 1 and the data sources in the appendix A.1. The average quarterly NTI as a proportion of total assets is 1.68bps, with a standard deviation of 7.42bps. The realized volatility can be significant for some banks with maximum and minimum values of 67bps and -77bps, respectively. Descriptive statistics for baseline risk factors show negative average values close to zero for the 3-month swap, oil returns and country-specific equity returns. Both oil and equity appear particularly volatile over the period, with quarterly standard deviations of 10.91 and 31.92 percent. Credit spreads (10Y-3M spread and BBB - 10Y spread) remain positive on average over the period.

3 Empirical Strategy

We map the macro-financial risk factors into the net trading revenues of banks using a fixed effects quantile dynamic regression model. We estimate the model semi-parametrically using the method of moments approach proposed by Machado and Silva (2019). The technique proves to be fast and reliable to estimate quantile panel data models with a large number of fixed effects without imposing the fixed effects to be quantile invariant, as in Koenker (2004) and Covas, Rump, and Zakrajšek (2014).[10] The estimation technique does not suffer from the incidental parameter problem if the ratio between the number of banks over the number of periods is strictly less than 10, like in our dataset. The specification that we use allows us

[10] Alternative computationally intensive techniques were introduced by Koenker (2004), Lamarche (2010), Canay (2011) and Galvao Jr (2011)

Table 1: Descriptive statistics (Reference period: 2015 Q2-2020 Q4.

Variables	N	Mean	SD	Min	P25	P50	P75	Max
Bank variables								
NTI on total assets(bps)	1242	1.68	7.42	-77.02	-0.47	0.98	3.55	67.04
REA on total assets(%)	1242	40.67	14.62	6.67	30.67	38.14	49.49	91.34
Equity on total assets(%)	1242	7.23	2.67	2.33	5.56	6.85	8.22	32.96
Baseline risk factors								
Stock returns(%)	299	-0.23	10.91	-107.28	-4.52	0.44	6.37	27.65
3M swap (%)	23	-0.32	0.12	-0.55	-0.37	-0.33	-0.31	-0.01
$(10Y - 3M)$ spread	23	0.02	0.23	-0.46	-0.24	0.09	0.21	0.42
EURO VSTOXX	23	3.01	0.34	2.49	2.73	2.90	3.26	3.88
Oil returns(%)	23	-0.18	31.92	-112.93	-7.37	5.39	15.88	64.42
ΔEuro/USD	23	0.01	0.04	-0.07	-0.02	0.01	0.04	0.08
$(BBB - 10Y)$ spread	23	1.29	0.46	0.62	1.09	1.25	1.52	2.86
Additional risk factors								
10Y Sovereign spread	299	0.19	0.67	-0.67	-0.30	-0.10	0.67	3.20
US VIX	23	2.84	0.39	2.25	2.59	2.75	3.12	3.98
Itraxx returns	23	-0.01	0.25	-0.36	-0.22	-0.05	0.18	0.77

Note: Source - ECB supervisory data, Bloomberg and ECB internal databases. **Bank level variables:** NTI over TA is total net trading revenue over total assets . REA over TA is total risk weighted assets over total assets. Equity over TA is total equity capital over total assets. **Core sample:** Equity returns are quarter over quarter returns for each country in the sample. Brent crude oil returns are measured as a quarterly percentage change. FX returns are measured as absolute changes in the EURUSD rate. The 3M swap is the euro area 3 month swap rate. The swap spread and BBB spread are spreads measured in levels and the Euro VStoxx variable is naturally logarithm of Vstoxx implied volatility index. **Additional Variables:** the sovereign spreads are the difference between the 10 year country yield over the 10 year euro area swap rate. The US Vix variable is naturally logarithm of 1 month S&P 500 implied volatility index. Finally, Itraxx returns are the quarter of over quarter returns of the Itraxx 5Y euro area financial index.

to overcome other potential shortcomings related to quantile regressions.[11] Moreover, the method proposed proved to be computationally fast even with a large number of fixed effects.

As mentioned in the previous section, we consider a large set of macro-financial risk factors in order to cover the main sources of risk for trading income: interest rate risk, credit risk, volatility risk, exchange rate risk, commodity price risk and equity price risk.

Our linear quantile fixed effect panel model belongs to the location-scale family models that in most general case are expressed as:

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

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: $Z_l = Z_l(X), l = 1, ..., k$;
- $\sigma(\cdot)$ is a known C^2 function of Z 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

$$E(U) = 0, E(|U|) = 1 \tag{2}$$

The model (1) implies that:

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

where $q(\tau) = F_U^{-1}(\tau)$ and $P(U < q(\tau)) = \tau$.[12]

[11] Fixed effects quantile regression models are notoriously difficult to estimate for three reasons. The first is that they are subject to the incidental parameter problem in short panels (i.e. when T<N). Second, quantile panel models are computationally intensive to estimate when the parameter space is large. Finally, the resulting estimates often lead to the quantile crossing problem.

[12] We denote with F the cumulative distribution function (CDF).

For our purposes, we consider a linear specification where $\sigma(\cdot)$ is the identity function and $Z = X$. Under these two assumption the model is simplified as follows:

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

where the regression quantile coefficient for variable l is:

$$\beta_l(\tau, X) = \beta_l + q(\tau) D^{\sigma}_{X_l} \tag{5}$$

with $D^{\sigma}_{X_l} = \frac{\partial \sigma(\delta + X'\gamma)}{\partial X_l} = \gamma_l$.

Using (2) and the exogeneity of the regressors, we can identify the vector of unknown parameters from the following set of moment conditions:[13]

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

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

In a sample of $(i = 1, 2, \ldots, N)$ European banks over the period (denoted as $t = 1, 2, \ldots, T$) and under the assumptions that $\sigma(\cdot)$ is the identity function and $Z = X$, then the location scale model of equation (1) is expressed as

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

[13] For simplicity here we assume i.i.d. data

At quantile t the model (6) implies that:

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

For model (6), the moment conditions have a convenient triangular structure with respect 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 $\left(X_{i,t} - \sum_t \frac{X_{i,t}}{T}\right)$ by OLS to get $\hat{\gamma}$;
- Estimate $\hat{\delta}_i = \frac{1}{T}\sum_t \left(|\hat{R_{i,t}}| - X_{i,t}'\hat{\gamma}\right)$;
- Finally use the estimated parameters as starting values and proceed by solving the following linear optimization problem:

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

  where the starting parameter values are replaced by the fitted values of the previous steps. ρ_τ is the standard check function and ω_τ are the weights for each τ.[14] For simplicity we assume equal weights across quantiles.

4 Baseline estimates

We estimate equation (7) for all quantiles ranging from 10th to 90th percentiles with 10 percentage points increments in the period 2015Q1-2020Q4.[15] Among the explanatory variables we include quarterly and bank-level fixed effects.[16] 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 in the vector of variables. We opt

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

[15] We 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).

[16] In Appendix C in table C.3 we show the regression estimates without quarterly dummies. The results are similar

for only two bank-specific characteristics to be considered in vector $X_{i,t}$ to keep the specifications relatively parsimonious. Our vector of explanatory variables also includes the lagged value of NTI/TA to account for the persistence in the trading activities.[17] Lastly, we add an array of exogenous risk factors reflecting macro-financial conditions. In the baseline estimates, the risk factors are the level and the slope of the yield curve proxied by the 3-month euro swap rate and the spread between the 10-year and 3-month euro swap rate, quarter over quarter stock returns at the country level, the spread between BBB corporates and the 10-year swap, quarter over quarter brent oil returns, the quarter returns between Euro-USD dollar exchange rate and the logged Vstoxx. Note that we only encompass 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. Starting with the OLS estimates, the entries of table 2 show that the lagged value of net trading income is significant but negative, indicating that banks can somewhat smooth Net trading income losses across quarters. Positive trading income today (weakly) predicts negative revenue in the next quarter. The other two significant financial indicators are stock returns and oil returns. Stock and oil returns contribute positively on average to net trading revenues.

Turning our attention now to the quantile estimates, we first notice that the degree of persistence does not vary markedly across quantiles. It is a surprising result, indicating that net trading income does not exhibit local persistence effects. Intuitively, it means that in the 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). The difference in lagged NTI/TA parameter between the top 10th and the 90th percentile is only 7bps.

On the other hand, financial variables exert significant and heterogeneous effects across percentiles. Besides the autoregressive component, the financial variables have no significant effect over higher quantiles. Yet, stock and oil returns show a positive effect on lower quantiles that are twice as high as the mean or median percentiles. The effect dissipates over quantiles and vanishes entirely at the 90th percentile. Intuitively, the distribution of NTI/TA becomes much more dispersed following a negative shock, with the conditional NTI/TA in higher quantiles being almost unaffected while at lower quantiles exhibiting significant

[17] The selection of a single lag stems from the AIC and BIC information criteria. The 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 in such settings should be small and not significantly affect the parameter estimates.

Table 2: OLS and Quantile Regression estimates on NTI

$Y_{i,t}$ = NTI on Total Assets$_t$	OLS	P10	P30	P50	P70	P90
NTI on Total Assets$_{t-1}$	-0.28***	-0.31**	-0.29***	-0.28***	-0.26***	-0.24***
	(0.07)	(0.14)	(0.09)	(0.07)	(0.06)	(0.08)
Equity on Total Assets$_{t-1}$	-12.75	-9.28	-11.48	-12.69	-13.91	-16.04
	(15.62)	(31.35)	(16.66)	(15.50)	(20.83)	(36.39)
REA on Total Assets$_{t-1}$	-5.19	-17.17*	-9.57	-5.41	-1.17	6.18
	(6.27)	(9.63)	(6.57)	(6.27)	(7.06)	(10.18)
3 Months Swap$_t$	-0.82	-1.03	-0.89	-0.82	-0.75	-0.62
	(2.09)	(4.63)	(2.64)	(2.09)	(2.36)	(4.09)
Swap Spread (10Y-3M)$_t$	-0.03	1.45	0.51	-0.00	-0.53	-1.43
	(1.12)	(1.29)	(1.07)	(1.10)	(1.24)	(1.59)
Credit Spread (BBB - 10Y)$_t$	-0.49	-2.30	-1.15	-0.52	0.12	1.24
	(1.26)	(1.75)	(1.32)	(1.27)	(1.38)	(1.84)
Stock returns$_t$	4.81**	9.22**	6.42**	4.89**	3.33	0.62
	(2.40)	(4.00)	(2.80)	(2.42)	(2.38)	(3.12)
Oil returns$_t$	2.20**	4.15**	2.92**	2.24**	1.55	0.35
	(0.87)	(2.08)	(1.14)	(0.88)	(0.97)	(1.73)
Δ EUR/USD$_t$	3.39	-2.31	1.31	3.28	5.30	8.80
	(5.90)	(6.18)	(5.71)	(5.86)	(6.30)	(7.51)
ln Euro Vstoxx$_t$	-0.70	-1.72	-1.07	-0.72	-0.36	0.26
	(0.97)	(1.28)	(0.82)	(0.97)	(1.33)	(2.14)
Bank fixed effects	**yes**	**yes**	**yes**	**yes**	**yes**	**yes**
Quarter fixed effects	**yes**	**yes**	**yes**	**yes**	**yes**	**yes**
Observations	1242	1242	1242	1242	1242	1242

Standard errors in parentheses

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

Note: Sample period: 2015:Q1–2020:Q4; No. of banks = 54;The dependent variable is the ratio of the Net trading income (NTI) over Total Assets (TA) in quarter . The entries in the column 2 of table are OLS estimates of the coefficients associated with the explanatory variables. The entries of columns P10, P30, P50, P70 and P90 corresponds to the 10th, 30th, 50th, 70th and 90th percentile estimates of the fixed effects panel quantile model estimated via the method of moments Machado and Silva (2019). Standard error-statistics reported in brackets are based on 1000 bootstrap standard errors clustered by bank.

losses.

Comparing our results with the one from Covas, Rump, and Zakrajšek (2014) for US banks, we can notice that the autoregressive coefficient does not show a statistically significant non-linearity across quantiles. This evidence might be explained based on the more pronounced stability of trading income for European banks. Moreover, this seems to suggest an essential difference between US and EU banks and might also be related to the more flexible specification used in our analysis.

5 Robustness checks

5.1 Sensitivity analysis

We complement our baseline estimates with a series of robustness checks. First, we estimate the fixed effects panel model for a shorter horizon in order to exclude the Covid-19 period that was characterized by the outbreak of the pandemic and the wide range of policy interventions. The Covid-19 shock hit the European markets around the first quarter of 2020, leading to an initial drop in several macroeconomic and financial variables with an (almost) immediate recovery. To assess how much the covid-19 pandemic influences the results, we restrict the sample up to the end of 2019, i.e. the pre-pandemic period. Table C.4 in the Appendix C shows the shorter sample estimates. The autoregressive lagged coefficient becomes much smaller in the pre-covid era and its impact is more pronounced in higher percentiles. This may reflect that banks in lower quantiles may take mitigating measures, such as hedging positions to offset any small fluctuations in market prices. Nonetheless, the sign of the coefficient remains negative and significant. Another interesting fact is that oil price movements have a significant positive effect in higher percentiles as opposed to the full sample estimates. These results indicate that, in normal times, financial factors affect mostly upside risks, whereas in periods of financial turmoil downside risks emerge.

We examine the potential contribution of other risk variables to NTI/TA. In particular, we replace equity returns with Itraxx senior financial returns, Vstoxx with VIX and we add, as an additional regressor, 10-year sovereign spreads for each country. Table C.5 in the Appendix C shows that the significance and persistence of net trading income lagged variables hardly change under this different specification. Swap spreads are turning significant at the two tails of the distribution, while itraxx senior financial takes all the significance from stock returns. Consistent with financial indicators, the Itraxx senior financial return is significant and negative for lower quantiles.

The fundamental distinction between our model and Covas, Rump, and Zakrajšek (2014) is that the latter considers a model where the individual fixed effects only cause parallel (location) shifts in the distribution of the response variable. In contrast, our approach is more general as it allows the individual fixed effects to affect the entire distribution if any $\delta_i \neq 0$. To check the suitability of our approach, we test the hypothesis that $\delta_i = 0 \; \forall$ i formally via an F-test. Conceptually, the null hypothesis is rejected if the constant of at least one bank varies across quantiles.

Formally, the model (6) nests the model of Covas, Rump, and Zakrajšek (2014) under the assumption that $\delta_i = 0 \; \forall$ i. Under this assumption, the equation 4 becomes

$$Q_{Y_{i,t}}(\tau|X_{i,t}) = \alpha_i + X'_{i,t} \underbrace{\Big(\beta + \gamma q(\tau)\Big)}_{\hat{\hat{\beta}}(q_\tau)} \tag{9}$$

At this point, we implement an F statistic test that the coefficients on the regressors $\hat{\delta}_i$ are all jointly zero. The hypothesis is rejected in all specifications.[18] This evidence supports the hypothesis that for European banks generalizing the model by Covas, Rump, and Zakrajšek (2014) is more adequate since banks seem to behave differently in different scenarios, making it even more important to depart from linear estimation methods for stress testing purposes.

5.2 In sample and out of sample performance

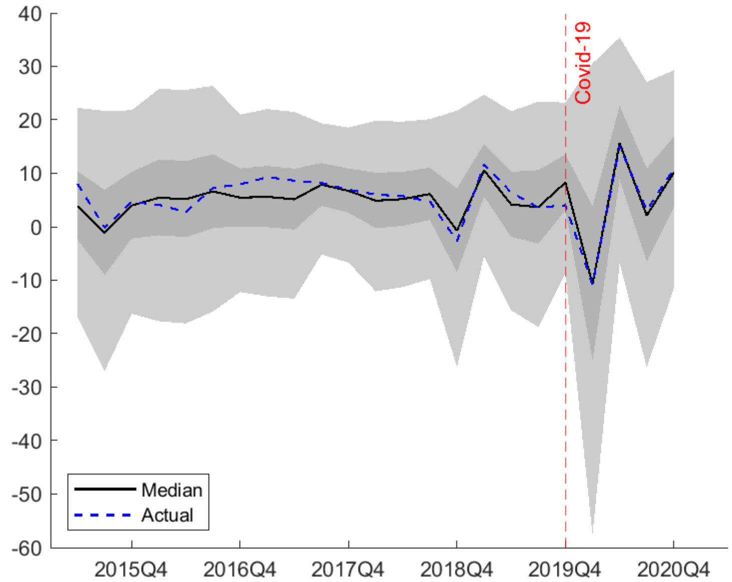
Figure 2 shows the fitted values of the conditional quantiles over time together with the average realized values across the sample of banks.[19] This figure confirms the goodness of fit of the model and illustrates the asymmetries over quantiles. Higher quantiles are stable over time, whereas lower quantiles vary significantly. We also look to individual banks and observe that while median/mean estimates accurately represent the net trading income ratio during normal times, they perform poorly during periods of financial distress. The realized value during the onset of the Covid-19 pandemic markedly deviates from the median and average

[18]Note that for simplicity, we compute the F-test under robust standard errors for the entire sample and not clustered across banks.

[19]We 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 percent quantiles to construct the α percent quantile of the group where $0 < \alpha < 1$. Therefore, if q_i is the α percent 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.

estimates in most of our sample banks. However, the realized values lie within the conditional distribution.

Figure 2: Fitted conditional quantile estimates and average realized NTI/TA

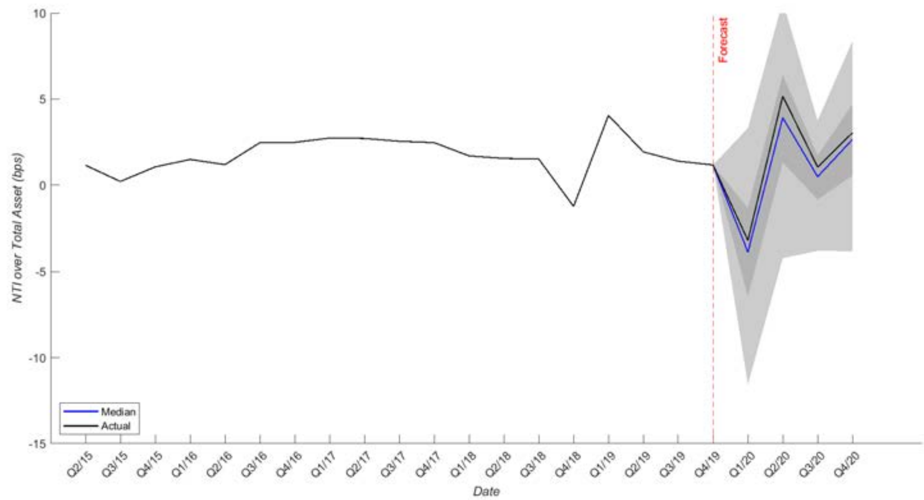


Note: The panel shows the estimates of NTI/TA (bps) over the period 2015-2020 at quarterly intervals for the aggregate sample of banks. The aggregate sample distribution is combined using vincentization - a quantile averaging method. The black line is the conditional median quantile, the shaded dark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

We also evaluate our methodology based on out-of-sample density forecasts during the period of the covid-19 crisis. First, we estimate the proposed quantile model using the actual data up to the last quarter of 2019. Then, we generate h-step ahead predictive NTI/TA distributions for each bank based on the estimated quantiles.

One challenge for our forecasting exercise is the non-recursive nature of the exercise. The data generating process of each of the exogenous variables included in $X_{i,t}$ is not specified. To circumvent this problem, we follow Covas, Rump, and Zakrajšek (2014) and we impose the exogenous variables $X_{i,t}$, to be equal to their respective realized values over h steps of the forecast. We begin by estimating the quantile fixed effects model using data from 2015Q1 up to 2019Q4 and iterate one quarter ahead forward to predict the conditional distribution of 2020Q1 for each bank. We then apply the same procedure, expanding the estimation sample, one quarter at a time, until the end of the sample 2020Q4. At each iteration we repeat the two-step procedure of sections 3 and 5. The outcome of this procedure will be one year out-of sample-density forecasts for each bank around the covid-19 shock and rebound.

Figure 3: conditional forecast density Q1 2020 to Q4 2020.



Note: Out of sample forecasted conditional distributions of NTI/TA (bps) averaged across the 54 banks.The aggregate sample distribution is combined using vincentization - a quantile averaging method. The black line is the realised values, the shaded dark gray defines the 30th to 70th forecasted quantiles and the lighter gray the 10th and 90th forecasted quantiles. The blue dashed line shows the median forcasted value averaged across banks.

Using the conditional quantile forecasts, we estimate the NTI distribution for the following 4 quarters. We estimate the tail risk measures and forecast expected losses across banks. The figure 3 shows the conditional forecast distribution of NTI/TA from Q2 2020 to Q1 2021. Overall, figure 3 illustrates that our two-step econometric approach generates robust predictive distributions, and is able to capture downside and upside vulnerabilities particularly well.

6 Conditional net trading income distribution

Based on our empirical model, we can compute the net trading income distribution and the expected shortfall and material loss probability conditional on a set of realized shocks or a hypothetical scenario. The quantile equation (3) delivers an approximate empirical inverse cumulative distribution function (CDF) of the NTI/TA ratio for each quarter and each bank.[20] Mapping the estimates of the quantile function into a

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

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 to fitted values of the quantiles computed based on our model:

$$f_Y(\mu, \sigma, \alpha, \nu) = \frac{2}{\sigma} t\big(\frac{y-\mu}{\sigma}; \nu\big) T \quad \alpha \frac{y-\mu}{\sigma} \sqrt{\frac{\nu+1}{\nu + \big(\frac{y-\mu}{\sigma}\big)^2}; \nu+1}\Bigg) \tag{10}$$

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 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 μ_t, σ_t, α_t, ν_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:

$$[\hat{\mu_t}, \hat{\sigma_t}, \hat{\alpha_t}, \hat{\nu_t}] = \underset{\mu,\sigma,\alpha,\nu}{\arg\min} \sum_{\tau} \Big(Q_{Y_t}(\tau|X_t) - F^{-1}_{Y_t}(\tau|\mu_t, \sigma_t, \alpha_t, \nu_t)\Big)^2 \tag{11}$$

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 the following quarter.

7 Conditional capital shortfall and material loss probability

So far, we use the method of moments to estimate the parameters of a quantile panel model with a large number of fixed effects (banks) and then we derive the empirical conditional distribution. In this section, we exemplify how the empirical distribution could be used to quantify the downside and upside risks to net trading income. The risks could be summarized by two tail risk measures - conditional expected shortfall and the material loss probability. For a given target percentile α the expected shortfall in the current period could be formally defined as follows

$$ES_t = \frac{1}{\alpha}\int_0^{\alpha} \hat{F}^{-1}_{y_t|X_t}(\tau|X_t)d\tau \tag{12}$$

where $\hat{F}^{-1}_{y_t|X_t}$ is computed according equation 11.

The counterparty equivalent for the upper tail - expected longrise is defined as

$$LR_t = \frac{1}{\alpha}\int_{1-\alpha}^{1} \hat{F}^{-1}_{y_t|X_t}(\tau|X_t)d\tau \tag{13}$$

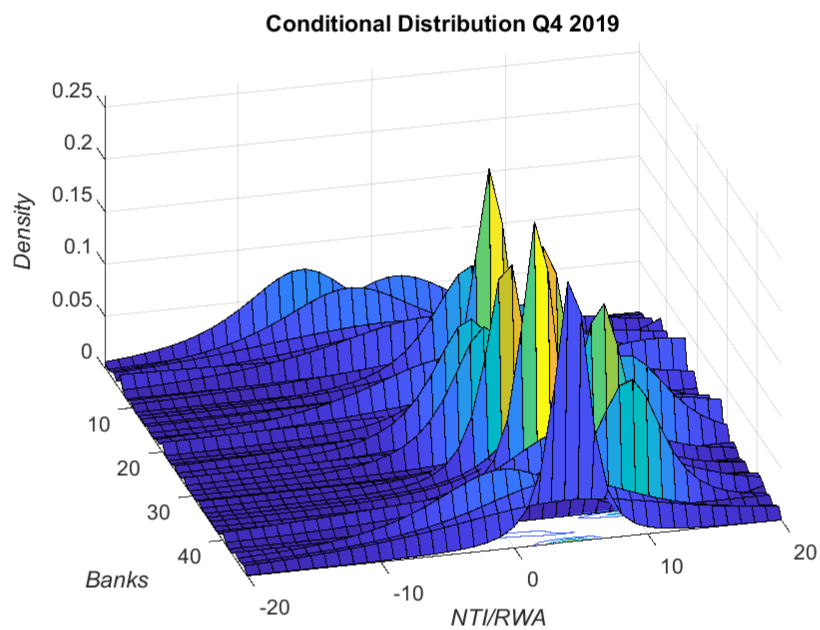
The 5% expected shortfall is the expectation of NTI ratio realization to be below the 5th percentile of the conditional distribution. To assess expected shortfalls and loss probabilities we measure NTI relative to RWAs to allow for comparison to CET1 ratios.[21],[22] In the spirit of EBA stress test exercise, we consider 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.

An alternative way of characterizing left tail risks is in terms of material loss probability, which is the likelihood that NTI losses exceed a certain threshold in the distribution. To estimate the material loss

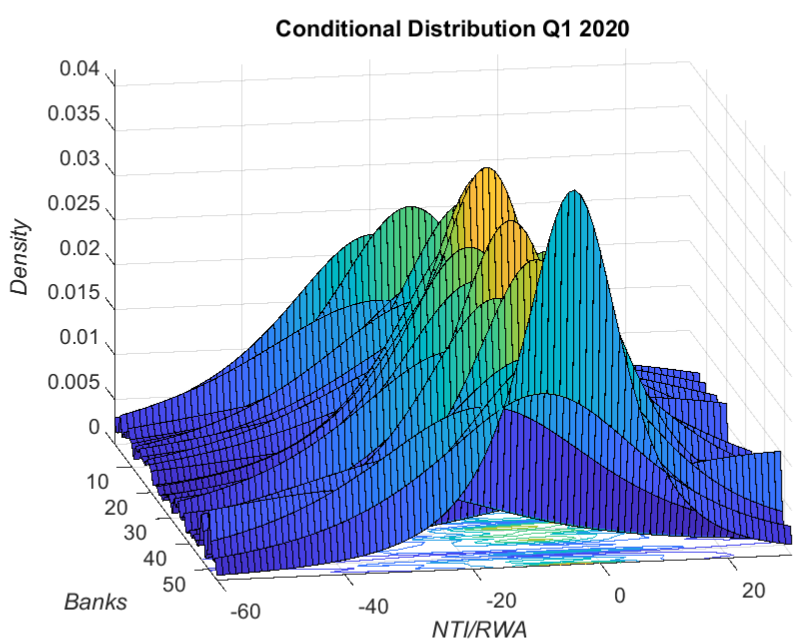
[21] In order to derive this ratio, we multiplied NTI by TA and divided it by RWA.

[22] The 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.

Figure 4: Conditional NTI/RWA 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/RWA. 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 has been restated relative to risk-weighted assets (RWA) so as to measure the expected impact on the bank CET1 ratio. NTI/RWA is presented in basis points.

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

$$MLP_t = Pr(-\infty < \tau < -15) = \int_{-\infty}^{-15bps} \hat{f}_{y_t|X_t}(\tau|X_t)d\tau \tag{14}$$

where $\hat{f}_{y_t|X_t}$ is the density of the fitted skewed t-distribution estimated according to equation 11.

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 50bps to 200bps 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 have a 10% expected capital shortfall greater than a material loss of 15bps RWAs. This means that if a bank experiences a tail loss, the expectation is that it will be material.

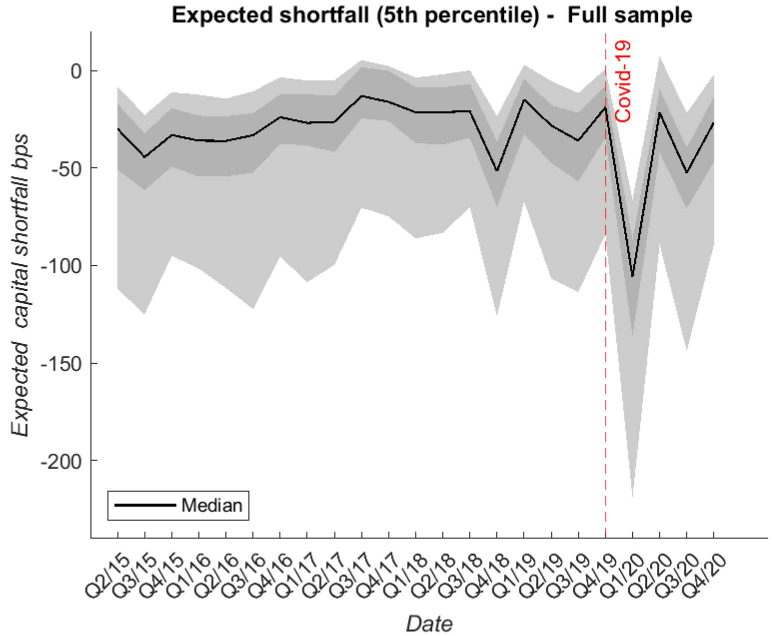
On the other hand, the upside risks summarized by expected longrise at the top 5th percentile are found to be more stable and less responsive to financial shocks. Figure 6 shows that even during the period of covid-19 upside risks increase by a modest of 10 bps for the median bank compared to 50 bps on the expected shortfall we saw in figure 5.

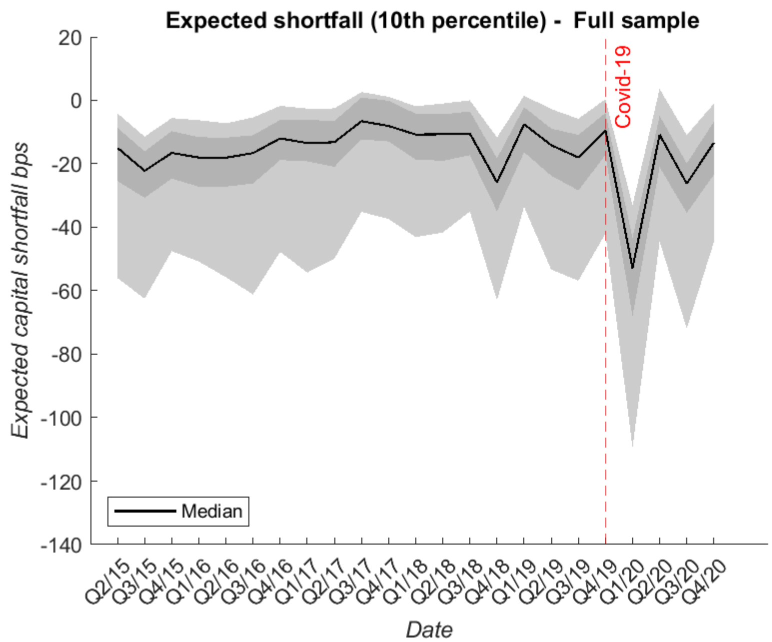
Lastly, figure 7 shows the probability of a material NTI loss across time. Overall, for the median bank the probability of a material loss is stable over time hovering around 10%. At the onset of the covid-19 crisis of there is a jump in probability to around 40% but this drops to 10% two quarters later. Overall, we can conclude that although downside and upside risks are somewhat correlated, downside risks are much more material and volatile to financial market developments.

8 Conclusion

Despite the rising contribution of non-interest income on banks' profitability, the risks associated with it to the banking sector are not well quantified. In this paper, we propose a new two-step econometric approach to measure the banks trading revenue vulnerability to financial shocks. First, we estimate a dynamic fixed effects quantile panel model using the method of moments approach (Machado and Silva (2019)). Then, based

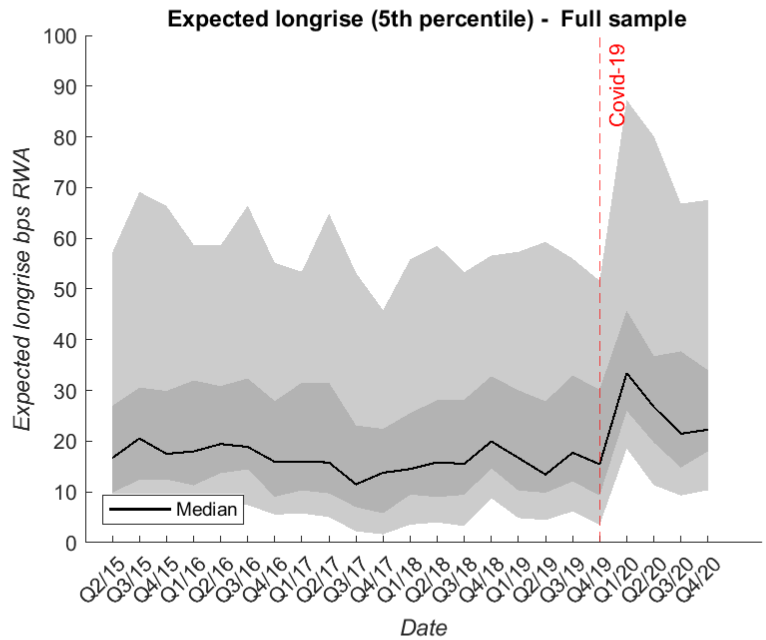
Figure 5: Conditional expected capital shortfall.





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 gray defines the banks at the 30th to 70th quantiles and the lighter gray the 10th and 90th quantiles. Expected shortfall is expressed in basis points of NTI/RWA.

Figure 6: Conditional expected capital longrise.



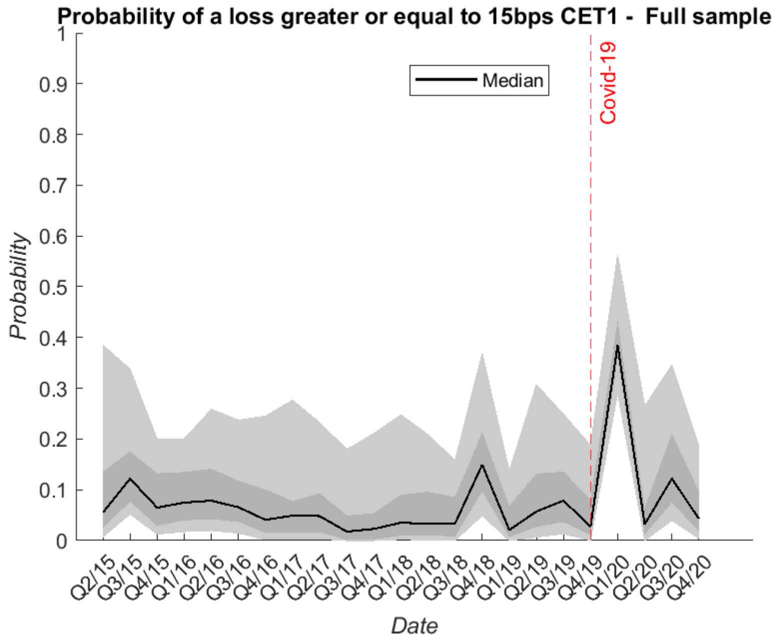
Note:The graph shows the conditional expected capital growth conditional on NTI/RWA being above the 95th percentile as defined in equation (12). Each quarterly observation on the graph shows the cross sectional distribution across the sample of banks. The black line represents the bank with the median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

on the model parameters we retrieve the entire conditional distribution by interpolating across quantiles as in Adrian, Boyarchenko, and Giannone (2019).

We show empirically the strong and asymmetric impact of financial risk factors on the distribution of NTI/TA across a large sample of European Banks. We find the left tail of the net trading income distribution is much more volatile and responsive to financial developments, whereas the right tail is much less responsive. Finally, we demonstrate how the methodology could be used to derive plausible measures and probabilities of a capital shortfall for stress test participating banks.

We argue that the model could be used by regulators as an additional tool in 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 of NTI considering the possible development of macro-financial variables and banks' characteristics.

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 gray defines the banks at the 30th to 70th quantiles and the lighter gray the 10th and 90th quantiles.

Our methodology could be also employed and extended in other interest and non-interest income sources such as commission fees and operating 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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Appendix A Variables Definitions and Sources

Table A.1: List and description of the variables

Variable	Source	Definition
Stock returns	ECB SDW	Quarter over quarter end of period equity returns of country-specific stock indices over the 2015Q1-2020Q4 period. The countries are: Austria, Belgium, Cyprus, Germany, Spain, Finland,France, Ireland, Italy, Luxembourg, Netherlands, Portugal, Slovenia.
Sovereign yields	ECB SDW	End of period quarterly yields by country over the 2015Q1-2020Q4 period. The countries are: Austria, Belgium, Cyprus, Germany, Spain, Finland,France, Ireland, Italy, Luxembourg, Netherlands, Portugal, Slovenia.
Itraxx returns	ECB SDW	Quarter over quarter end of period itraxx returns. Itraxx 5 year Euro area financial index.
ln Euro Vstoxx	ECB SDW	The natural logarithmic of the Vstoxx Index. Vstoxx is an option derived implied volatility index.
ln VIX	ECB SDW	The natural logarithmic of the CBOE 1 month volatility Index . VIX is an option derived implied volatility index of the S&P 500 index.
3MSwap	Bloomberg	European interest rate swap with 3 months maturity Bloomberg ticker EUSWC Curncy.
10YSwap	Bloomberg	European interest rate swap with 10 years maturity Bloomberg ticker EUSA10 Curncy.
Swap Spread (10Y-3M)	Bloomberg	The spread between European interest rate swap with 10 years and 3 months maturity.
Credit Spread (BBB-10Y)	Bloomberg	The spread between BBB Corporate yields financial with 10 years interest rate european swap
OIL returns	Bloomberg	Quarter over quarter brent crude oil index returns. The Bloomberg ticker is EUCRBRDT Index
Δ Euro/USD	Bloomberg	The quarter over quarter difference between Euro/USD dollar exchange rate. The Bloomberg ticker is EURUSD Curncy

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 (2015-2020). 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.2 shows the distribution of our sample banks by country, size and the coverage of the banking system's total assets.

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 or are closed during the sample period possibly leading to a sample selection bias. We argue that our reference period is somewhat short and hence the sample selection bias, if any, is rather small. Second, some of the sample banks trade on a global scale and in multiple financial markets, hence are influenced by international financial conditions. For this reason, we include bank specific quantile variant fixed effects to control for any scale effects and other unobserved time invariant bank specific heterogeneity. Finally, our time span is relatively short but does include the recent market volatility during the Covid-19 crisis and recovery.

Table B.2: 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

Appendix C Robustness Checks

Table C.3: OLS and Quantile Regression estimates not quarterly dummies

$Y_{i,t}$ = NTI on Total Assets$_t$	OLS	P10	P30	P50	P70	P90
NTI on Total Assets$_{t-1}$	-0.27***	-0.31**	-0.28***	-0.27***	-0.27***	-0.25***
	(0.07)	(0.14)	(0.09)	(0.07)	(0.06)	(0.09)
Equity on Total Assets $_{t-1}$	-12.08	-8.61	-10.98	-12.01	-13.06	-15.01
	(15.21)	(33.81)	(16.57)	(15.10)	(20.07)	(35.65)
REA on Total Assets$_{t-1}$	-4.91	-18.89*	-9.35	-5.18	-0.94	6.90
	(6.21)	(10.38)	(6.53)	(6.19)	(6.89)	(9.98)
3 Months Swap$_t$	-0.42	1.94	0.33	-0.37	-1.09	-2.41
	(2.14)	(5.35)	(2.77)	(2.15)	(2.36)	(4.18)
Swap Spread (10Y-3M)$_t$	0.34	1.55	0.73	0.37	-0.00	-0.68
	(1.09)	(1.35)	(1.09)	(1.08)	(1.16)	(1.44)
Credit Spread (BBB - 10Y)$_t$	0.39	-0.72	0.04	0.36	0.70	1.32
	(1.24)	(1.77)	(1.25)	(1.24)	(1.38)	(1.89)
Stock returns$_t$	4.40**	7.38*	5.34**	4.46**	3.55	1.88
	(2.21)	(4.10)	(2.62)	(2.23)	(2.18)	(2.98)
Oil returns$_t$	2.67***	5.54**	3.58***	2.72***	1.85**	0.24
	(0.78)	(2.42)	(1.14)	(0.80)	(0.88)	(1.75)
ΔEUR/USD$_t$	7.12	5.54	6.62	7.09	7.56	8.45
	(5.52)	(6.39)	(5.55)	(5.51)	(5.71)	(6.59)
ln EURO Vstoxx$_t$	-1.20	-3.70**	-1.99**	-1.25	-0.49	0.91
	(0.93)	(1.51)	(0.86)	(0.94)	(1.24)	(2.04)
Observations	1242	1242	1242	1242	1242	1242

Note: Standard errors in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Sample period: Q1 2015 - Q4 2020. The dependent variable is the ratio of the Net trading income (NTI) over Total Assets (TA) in quarter . The entries in the column 2 of table are OLS estimates of the coefficients associated with the explanatory variables. The entries of columns P10, P30, P50, P70 and P90 corresponds to the 10th, 30th, 50th, 70th and 90th percentile estimates of the fixed effects panel quantile model estimated via the method of moments Machado and Silva (2019). Standard error-statistics reported in brackets are based on 1000 bootstrap standard errors clustered by bank.

Table C.4: OLS and Quantile Regression estimates

$Y_{i,t}$ = NTI on Total Assets$_t$	OLS	P10	P30	P50	P70	P90
NTI on Total Assets$_{t-1}$	-0.13***	-0.07	-0.11***	-0.13***	-0.15***	-0.19**
	(0.04)	(0.08)	(0.04)	(0.04)	(0.05)	(0.09)
Equity on Total Assets$_{t-1}$	-3.31	-15.25	-7.27	-3.29	0.66	7.92
	(15.94)	(30.89)	(17.56)	(15.94)	(20.11)	(34.45)
REA on Total Assets$_{t-1}$	-1.02	-8.55	-3.52	-1.01	1.48	6.06
	(5.94)	(9.86)	(6.68)	(5.92)	(6.17)	(8.43)
3 Months Swap	0.90	-4.10	-0.76	0.91	2.56	5.60
	(3.55)	(5.72)	(3.91)	(3.55)	(3.81)	(5.36)
Swap Spread (10Y-3M)$_t$	0.21	1.03	0.48	0.21	-0.07	-0.57
	(0.78)	(1.38)	(0.88)	(0.77)	(0.85)	(1.29)
Credit Spread (BBB - 10Y)$_t$	-0.02	-2.19	-0.74	-0.02	0.70	2.02
	(0.91)	(1.35)	(0.92)	(0.93)	(1.10)	(1.62)
Stock returns$_t$	8.23***	10.40*	8.95**	8.23***	7.52***	6.20*
	(2.91)	(5.52)	(3.62)	(2.92)	(2.69)	(3.59)
Oil returns$_t$	1.76*	-0.45	1.03	1.76*	2.50**	3.84**
	(1.00)	(1.97)	(1.20)	(0.99)	(1.06)	(1.75)
Δ EUR/USD$_t$	3.37	-4.36	0.81	3.38	5.94	10.64
	(6.11)	(6.93)	(6.06)	(6.05)	(6.42)	(7.78)
ln EURO Vstoxx $_t$	-1.17	-1.51	-1.28	-1.17	-1.05	-0.85
	(1.69)	(2.49)	(1.70)	(1.69)	(2.00)	(3.00)
Bank fixed effects	**yes**	**yes**	**yes**	**yes**	**yes**	**yes**
Quarter fixed effects	**yes**	**yes**	**yes**	**yes**	**yes**	**yes**
Observations	1026	1026	1026	1026	1026	1026

Standard errors in parentheses

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

Note: Sample period: 2015:Q1–2019:Q4; No. of banks = 54;The dependent variable is the ratio of the Net trading income (NTI) over Total Assets (TA) in quarter . The entries in the column 2 of table are OLS estimates of the coefficients associated with the explanatory variables. The entries of columns P10, P30, P50, P70 and P90 corresponds to the 10th, 30th, 50th, 70th and 90th percentile estimates of the fixed effects panel quantile model estimated via the method of moments Machado and Silva (2019). Standard error-statistics reported in brackets are based on 1000 bootstrap standard errors clustered by bank.

Table C.5: OLS and Quantile Regression estimates

$Y_{i,t}$ = NTI on Total Assets$_t$	OLS	P10	P30	P50	P70	P90
NTI on Total Assets$_{t-1}$	-0.27***	-0.30**	-0.28***	-0.27***	-0.26***	-0.25***
	(0.07)	(0.14)	(0.09)	(0.07)	(0.06)	(0.08)
Equity on Total Assets$_{t-1}$	-9.16	-8.93	-9.09	-9.16	-9.23	-9.37
	(13.47)	(29.77)	(16.27)	(13.43)	(15.83)	(27.49)
REA on Total Assets$_{t-1}$	-5.78	-19.82*	-10.33	-5.78	-1.45	6.99
	(6.55)	(10.44)	(7.01)	(6.56)	(7.22)	(10.31)
3 Months Swap$_t$	-1.90	-3.75	-2.50	-1.90	-1.33	-0.21
	(1.74)	(3.81)	(2.16)	(1.72)	(1.95)	(3.41)
Swap Spread (10Y-3M)$_t$	0.62	4.55***	1.90***	0.63	-0.58	-2.94**
	(0.60)	(1.05)	(0.58)	(0.60)	(0.80)	(1.31)
Itraxx growth	-1.82	-4.56***	-2.71**	-1.82	-0.98	0.66
	(1.38)	(1.67)	(1.24)	(1.39)	(1.69)	(2.55)
Stock returns$_t$	3.60	8.37*	5.14	3.60	2.13	-0.74
	(2.96)	(4.37)	(3.28)	(2.97)	(2.94)	(3.53)
Oil returns$_t$	1.90**	3.95*	2.56**	1.90**	1.26	0.03
	(0.92)	(2.06)	(1.22)	(0.92)	(0.85)	(1.35)
Δ EUR/USD$_t$	1.22	-4.86	-0.75	1.21	3.09	6.73
	(6.41)	(6.58)	(6.11)	(6.40)	(6.98)	(8.60)
ln US Vix$_t$	-0.52	-0.78	-0.60	-0.52	-0.44	-0.28
	(0.78)	(1.56)	(0.95)	(0.78)	(0.81)	(1.28)
10Y Sovereign spread$_t$	0.50	-1.00	0.01	0.50	0.96	1.87
	(0.58)	(0.71)	(0.46)	(0.59)	(0.81)	(1.31)
Bank fixed effects	**yes**	**yes**	**yes**	**yes**	**yes**	**yes**
Quarter fixed effects	**yes**	**yes**	**yes**	**yes**	**yes**	**yes**
Observations	1242	1242	1242	1242	1242	1242

Standard errors in parentheses

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

Note: Sample period: 2015:Q1–2020:Q4; No. of banks = 54; The dependent variable is the ratio of the Net trading income (NTI) over Total Assets (TA) in quarter . The entries in the column 2 of table are OLS estimates of the coefficients associated with the explanatory variables. The entries of columns P10, P30, P50, P70 and P90 corresponds to the 10th, 30th, 50th, 70th and 90th percentile estimates of the fixed effects panel quantile model estimated via the method of moments Machado and Silva (2019). Standard error-statistics reported in brackets are based on 1000 bootstrap standard errors clustered by bank.

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