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Macro stress testing euro area banks' fees and commissions

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Abstract

This paper uses panel econometric techniques to estimate a macro-financial model for fee and commission income over total assets for a broad sample of euro area banks. Using the estimated parameters, it conducts a scenario analysis projecting the fee and commission income ratio over a three years horizon conditional on the baseline and adverse macroeconomic scenarios used in the 2016 EU-wide stress test. The results indicate that the fee and commission income ratio is varying in particular with changes in its own lag, the short-term interest rate, stock market returns and real GDP growth. They also show that the fee and commission income ratio projections are more conservative under the adverse scenario than under the baseline scenario. These findings suggest that stress tests assuming scenario-independent fee and commission income projections are likely to be flawed.

KEYWORDS: Fee and commission income, stress testing, scenario analysis
JEL CLASSIFICATION: G21, G17, G01

Non-Technical Summary

The recent financial and sovereign debt crises highlighted the importance for economic activity of having sound banks able to withstand extreme and unexpected shocks to their balance sheets and able to generate sufficient income even in times of distress. Indeed, banks resilient to stress and able to act as effective financial intermediaries over the economic cycle are a necessary condition for ensuring a smooth flow of credit to the real economy also in periods of economic turbulence. With the aim of ensuring a well-functioning financial system to support economic growth, macro stress-testing frameworks are often used to assess in a forward-looking manner the resilience of the banking sector to (adverse) macroeconomic and financial developments.

The main purpose of macro stress testing is to assess the sensitivity to adverse macroeconomic and financial developments of individual banks' balance sheet and profits and losses. While most stress testing tools typically have well-developed modules for projecting loan losses and net interest income, other sources of income and expenses are often only modelled in a rudimentary fashion. This ignores that other parts of banks' net income may be also related to macroeconomic and financial developments. In other words, these stress testing approaches may risk overlooking key elements of banks' income generating activities, such as income from fees and commissions which together with net interest income and net trading income are the three most important income sources for most banks. In fact, fees and commissions constitute on average between 22% and 30% of euro area banks' net revenue and about two thirds of euro area banks' total non-interest income. Therefore, stress tests that ignore the sensitivity to macroeconomic conditions of such an important income source may potentially underestimate the volatility of banks' solvency position when exposed to stress events.

Against this background, this paper proposes a model for estimating the relationship between some key macroeconomic and financial factors and fee and commission income over assets, using yearly data between 1995 and 2015 for a large sample of euro area banks. Then, it shows how the estimated model can be applied to stress test the resilience of this source of revenue conditional on the baseline and adverse macroeconomic scenarios used in the 2016 EU-wide stress test.

More specifically, the empirical strategy adopted in this paper begins with the selection, out of a predetermined group of macroeconomic and financial factors, of the independent variables that have the most explanatory power for fee and commission over assets, our variable of interest. This selection approach yields as the most relevant drivers the lag of fee and commission income over total assets, the lag of the first difference of the short term interest rate, the stock market returns (both the lagged and the contemporaneous variable), the lag of the first difference of the long term interest rate, residential property price growth and the real GDP growth. In a second step, a model for fees and commissions over assets including the selected regressors is estimated. The results show that lagged fee and commission income over assets, the contemporaneous stock market returns and real GDP growth are positively and significantly related to fees and commissions over assets, while the first difference of the short term interest rate is negatively and significantly associated to our variable of interest. Finally, this study provides a scenario analysis

which highlights the usefulness of the estimated model in a stress-testing context. Indeed, the estimated parameters are used to project fee and commission income over assets over a three year horizon conditional on both a baseline and an adverse macroeconomic scenario. This scenario analysis illustrates how fees and commissions over assets, aggregated at country level for 18 euro area countries, are sensitive to the different macroeconomic developments. Indeed, the resulting fees and commissions projections are considerably more conservative under the adverse scenario than under the baseline scenario.

This paper contributes to the existing limited literature on the topic in several ways. First, combining bank-level and macroeconomic data, it studies the determinants of fees and commissions as a ratio of total assets at the international level while most of the related studies have investigated this issue at the country level. The international analysis is useful as provides for a larger size of the panel and it allows for assessing country-specific differences in fee and commission income dynamics. Second, it relies on a sound statistical technique to select, out of a predetermined set of macroeconomic and financial factors, the determinants of fees and commissions over assets to be included in the benchmark model. The application of this selection strategy is particularly relevant because it reduces the degree of discretion in the choice of the key explanatory factors. Finally, this work, relying on different econometric approaches to estimate the relationship between our variable of interest and the selected macroeconomic and financial factors, provides the necessary degree of robustness.

1 Introduction

The recent financial and sovereign debt crises highlighted the importance for economic activity of having sound banks able to withstand extreme and unexpected shocks to their balance sheets and able to generate sufficient income even in times of distress. Indeed, banks resilient to stress and able to act as effective financial intermediaries over the economic cycle are a necessary condition for ensuring a smooth flow of credit to the real economy also in periods of economic turbulence. With the aim of ensuring a well-functioning financial system to support economic growth, macro stress-testing frameworks are often used to assess in a forward-looking manner the resilience of the banking sector to (adverse) macroeconomic and financial developments, see e.g. the studies by Henry and Kok (2013) outlining the European Central Bank (ECB) top-down stress testing framework and by Borio, Drehmann and Tsatsaronis (2014) discussing strength and weaknesses of macro stress testing in general.

The main purpose of macro stress testing is to assess the sensitivity to adverse macroeconomic and financial developments of individual banks' balance sheets and profits and losses. The topic has received substantial attention in recent years and sophisticated methods have been developed to provide sufficiently robust and conservative model predictions; see e.g. Gross and Población (2015) who promote the use of Bayesian model averaging. While most stress testing tools typically have well-developed modules for projecting loan losses and net interest income, other sources of income and expenses are typically only modelled in a rudimentary fashion. This ignores that other parts of banks' net income may be also related to macroeconomic and financial developments. In other words, these stress testing approaches may risk overlooking key elements of banks' income generating activities, such as income from fees and commissions which together with net interest income and net trading income are the three most important income sources for most banks. In fact, fees and commissions constitute on average between 25% and 30% of euro area banks' total income and about two thirds of euro area banks' total non-interest income. Therefore, stress tests that ignore the sensitivity to macroeconomic conditions of such an important income source may potentially underestimate the volatility of banks' solvency position when exposed to stress events.

Against this background, this paper proposes a model for estimating the relationship between some key macroeconomic and financial factors and fee and commission income over assets, using yearly data between 1995 and 2015 for a large sample of euro area banks. Then, it shows how the estimated model can be applied to stress test the resilience of this source of revenue under both a baseline and an adverse macroeconomic scenario.

While substantial research efforts have been directed at modelling banks' balance sheets and at forecasting loan losses and net interest income components, only few studies have focused on fee and commission income despite its significance as the second most important source of revenue for the majority of European banks. Perhaps owing to the scarcity of empirical studies on the determinants of fees and commissions and to the fact that fee and commission income tends to be less volatile than the other main streams of bank revenue (e.g. net interest income),

this income component is often assumed to be stable in forward-looking analyses such as stress tests. However, this assumption may often end up being over-simplistic because a relative stability may not necessarily imply an absence of cyclical fluctuations. In fact, notwithstanding the limited relative volatility, fee and commission income has proven to exhibit pronounced cyclical tendencies in some cases. Fee and commission income of euro area significant banking groups has generally tended to correlate strongly with net interest income over the last few years.[1] This seems to suggest that both sources of income are driven by some common underlying factors, such as broad macroeconomic activity and retail customer business activities.[2] Activities of a cyclical nature probably relate to economic and financial market activities, such as financial services (including those to retail customers), securities and loan underwriting, advisory services related to mergers and acquisitions (M&A) and securities brokerage business. However, also more structural factors, such as payment transactions, safe custody administration and bank competition, are likely to be important determinants of overall fee and commission income. By contrast, the movement of fee and commission income in relation to trading income has been more heterogeneous across banks in the significant banking groups sample.[3]

The empirical literature aiming to measure the cyclical variation in non-interest income subcomponents was pioneered by Saunders and Walter (1994) and Kwan and Laderman (1999). These studies find that fee and commission activities provide stability to banks' income contrary to trading activities. ECB (2000) finds similar results for EU banks but it goes one step further by making a distinction, within fee and commission income, between the so called traditional fee-generating banking activities and more market-related businesses in which banks expanded heavily in recent decades (e.g. brokerage, M&A, underwriting). Fee and commission income from traditional banking appears to be less subject to cyclical variations compared to that generated by recent activities. Smith, Staikouras and Wood (2003) also highlight that non-interest income activities are less volatile than net interest income for a panel of EU banks between 1994 and 1998. Overall, the results of the literature which studies the relationship between non-interest income and banks' financial performance, as well as risk-taking are not conclusive.

Possibly, the closest study in spirit to ours is Coffinet, Lin and Martin (2009) who exploit a large data set of French banking supervisory data between 1993 and 2007. Coffinet et al. (2009) first detect the determinants of the three main components of banks' revenues, i.e. net interest income, fees and commissions and trading income, and then assess the sensitivity of these sources of income to macroeconomic and financial developments, stress testing their resilience to several scenarios. As regards the main drivers of fee and commission income, using

[1] See also the evidence provided in ECB (2013b).

[2] This is not surprising as many products offered by banks have both an interest rate and a fee component (e.g. customer accounts and various forms of credit agreements).

[3] This may reflect the fact that, although trading activity can trigger fee and commission income, it can be highly volatile (on account of price valuation adjustments) during periods of turbulence that do not necessarily affect banks' trading-related fees and commissions (which are linked to business volumes). Although such an imperfect correlation may suggest some potential diversification effects, the findings of the academic literature are ambiguous in this regard (see, for example, Stiroh and Rumble (2006)).

a dynamic panel approach, Coffinet et al. (2009) show that GDP growth, stock market returns and expenditures over total assets exhibit a positive and significant relationship while the ratio of loan loss provisions over total loans (a measure of banks' risk taking) is negatively related to this source of income. The study also shows that lagged trading income has a positive impact on current fee and commission income. Finally, the authors somewhat surprisingly find that fees and commissions are more sensitive to adverse macroeconomic developments than interest income.

In a related study, Lehmann and Manz (2006) likewise investigate which macroeconomic variables play a role in explaining the earnings of the banking sector. Exploiting Swiss banking data between 1994 and 2007, they study the main determinants of four components of banks' earnings, i.e. net interest income, provisions, trading income and commission income, and assess their sensitivity to different economic scenarios. In relation to the latter source of income, their results show that lagged commissions and positive stock market returns are positively associated with higher commission income while stock market volatility is negatively associated with this source of income.

Albertazzi and Gambacorta (2009) investigate the relation between bank profitability at country level and the business cycle by using annual data for 10 advanced economies between 1981 and 2003. Using a GMM estimator as suggested by Arellano and Bond (1991), they find that non-interest income is positively and significantly related to its own lag, to stock market volatility and the inflation rate, while negatively and significantly related to long-term interest rates. Their empirical evidence also shows that GDP growth is not a significant driver of this source of income.

Hirtle, Kovner, Vickery and Bhanot (2014) introduce a top-down stress-test model (called CLASS, i.e. Capital and Loss Assessment under Stress Scenarios) to assess the impact of severe macroeconomic developments on the performance and capital positions of US banks. In this context, using publicly available data, they show that non-trading non-interest income over total assets exhibit a positive significant relationship with its own lag, stock market returns and the share of credit card loans over interest earning assets while it exhibits a negative and significant relationship with the share of commercial real estate loans over interest earning assets and the share of the banks assets over the total industrys assets.

Covas, Rump and Zakrajsek (2014) propose a fixed-effect quantile autoregressive approach to study the effects of adverse macroeconomic scenarios on the capital positions of the 15 largest US banks. Using publicly available quarterly data from 1997 to 2011, they find that non-trading non-interest income over consolidated assets is positively and significantly associated with its own lags while it is negatively and significantly related to three-month Treasury yield and to corporate bond credit spreads.

Finally, in the context of the literature that studies the implications of banks income diversification on banks risk taking, DeYoung and Rice (2004) and Busch and Kick (2009) also provide empirical evidence on the determinants of non-interest income.

DeYoung and Rice (2004), exploiting data for a large panel of urban US commercial banks between 1989 and 2001, show that non-interest income is significantly associated with a number of bank-specific factors, market conditions and technological developments. Specifically, they find that well-managed banks, measured by a high relative return on equity (ROE), rely less on non-interest income while large banks and banks that focus more on relationship banking are more reliant on non-interest income. Moreover, they show that an increase in non-interest income is related to higher and more volatile profits and an overall worsening of the risk-return trade-off for the average commercial bank during the considered sample period.

Busch and Kick (2009) study the determinants of non-interest income and the impact of this income source on the performance of German banks between 1995 and 2007 using yearly supervisory data. Their work shows that banks relying more on traditional banking relationships, holding a higher amount of equity over assets and having a higher service intensity are more concentrated in the fees and commissions business. Furthermore, they find that a larger share of fee income over total income is positively and significantly associated with higher risk-adjusted return on equity (ROE) and on total assets (ROA). However, for commercial banks they provide evidence that a strong involvement in fee-generating activities is associated with higher risk.

This paper contributes to the existing limited literature in several ways. First, combining bank-level and macroeconomic data, it studies the determinants of fees and commissions as a ratio to total assets and stresses this source of income at the international level while most of the related studies have investigated this issue at the country level. The international analysis is useful as it provides for a larger size of the panel and allows for assessing country-specific differences in fee and commission income dynamics. Second, it relies on a sound statistical technique (i.e. the Least Angle Regression procedure (LARS) developed by Efron, Hastie, Johnstone and Tibshirani (2004)) to select, out of a predetermined set of macroeconomic and financial factors, the determinants of fees and commissions over assets to be included in the benchmark model. The application of this selection strategy is particularly relevant because it reduces the degree of discretion in the choice of the key explanatory factors. This is similar in spirit to the approach by Kapinos and Mitnik (2016), who employ the Least Absolut Shrinkage and Selection Operator (LASSO), which is a constrained version of LARS, in a stress testing framework. Finally, our study hinges on four different econometric approaches to estimate the drivers of fees and commissions over assets and, thus, provides the necessary degree of robustness.

Our empirical strategy begins with the selection, out of a predetermined group of macroeconomic and financial factors[4], of the independent variables that have the most explanatory power for fees and commission over assets. To this end, we exploit the LARS procedure developed by Efron et al. (2004). Then, in a second stage, we estimate a benchmark model according to 4 different econometric methods: we employ a feasible generalised least square (FGLS) estimator,

[4]In this analysis, we only consider macroeconomic and financial variables as possible explanatory factors of fee and commission income over assets as these are the variables which are typically included in stress test scenarios.

a fixed effects (FE) model, a system generalized methods of moment (GMM) estimator (Blundell and Bond 1998) and a bias-corrected least squares dummy variable (LSDVC) estimator as implemented by (Bruno 2005a,b). The latter method represents our preferred approach since it corrects for dynamic panel bias, induced by the inclusion of the lagged dependent variable among the selected regressors, while still allowing for the explicit estimation of bank fixed effects.

Our benchmark estimates, using as explanatory variables the lag of the dependent variable, the stock market returns (both lagged and contemporaneous value), GDP growth, both the lag of the first difference of the short-term and long-term interest rates and the residential property price growth, show that the signs of the estimated coefficients are all as expected when significant and broadly in line with the previous literature. More specifically, our results show that lagged fee and commission income over assets, stock market returns and GDP growth are positively and significantly related to fees and commissions over assets, while the first difference of the short-term interest rate is negatively and significantly associated with our dependent variable. The other variables are insignificant. Against this background, it is important to stress that the different econometric methods adopted yield qualitatively similar results. The results are also resilient to a set of robustness checks.

Finally, as a last step of our investigation, we conduct a scenario analysis. We use the estimated parameters to project fee and commission income over assets over a three-year horizon (between 2016 and 2018) conditional on both the baseline and adverse financial and macroeconomic scenarios used in the 2016 EU-wide stress test exercise coordinated by the European Banking Authority (EBA). This scenario analysis illustrates how fees and commissions are sensitive to the different macroeconomic developments. Indeed, the resulting fee and commission projections aggregated at country level are considerably more conservative under the adverse scenario than under the baseline scenario. More specifically, the projected fee and commission income ratios feature, at country level, an overall decline with respect to the 2015 starting point under the adverse scenario for the majority of countries. By contrast, baseline projections exhibit either a steady or an increasing path with respect to the 2015 cut-off level for most of the countries.

The rest of this paper is organized as follows. In Section 2, we describe the dataset we use in our analysis. In Section 3, we present some descriptive information for the key variables of interest; Section 4 outlines the applied variable selection procedure. Section 5 reports the adopted econometric approaches, displays and discusses our main findings, and briefly describes the implemented battery of robustness checks. Section 6 illustrates the scenario analysis that we conduct according to both a baseline and an adverse scenario. A final section concludes.

2 Data

In this study, we use an unbalanced panel of annual data from 1995 to 2015 for a sample of banks which are mostly subject to the direct supervision of the Single Supervisory Mechanism

(SSM) and are established in all 19 euro area countries.[5] The banking data were extracted from Bloomberg. After excluding from the sample the banks for which less than 5 years of observations are available, the dataset includes 103 banks.[6] The most represented countries are Germany (20 banks), Italy (14 banks), Spain (12 banks) and France (10 banks). One country, namely Estonia, has only one banking institution in the sample. As expected, the coverage of banks tends to increase over time, i.e. the most recent years typically have the best coverage.[7] Table A.2 and Table A.3 provide the number of banks available in the sample respectively by country and by year.

The bank-specific variables included in our sample are both from banks' income statements and balance sheets.[8] In particular, from banks' income statements we obtain information about the variable of interest, i.e. fee and commission income. This item includes revenues earned from a range of activities, i.e. service charges, loan servicing fees, brokerage fees, trust fees and management fees. In this work, we only aim to model income from fees and commissions since it is the main component of the broader non-interest income class which comprises revenues from very heterogeneous activities. From banks' balance sheet, we extract information about total assets.

The dataset set used in this study also includes a series of macroeconomic and financial variables for the considered 19 euro area countries.[9] The set of explanatory variables was selected to reflect variables considered in the literature and also taking into account the need to include only variables that are projected in stress testing scenarios.

Finally, Table A.6 reports the main summary statistics of the used variables.

3 Some stylised facts

In the last decades, higher competition on traditional intermediation activities strengthened banks' incentives to develop non-interest income business activities.[10] Specifically, several studies have emphasised the relevance of fees and commissions as a source of revenue for banks. ECB (2010) and ECB (2013a) show that the mean ratio of net fee and commission income to total assets of a sample of large euro area banks was between 0.4% and 0.6% in the second half of the last decade. ECB (2013b) shows that the median ratio of net fee and commission income

[5]The 19 countries taken into account in the analysis, as shown in Table A.2, are Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Portugal, Spain, Slovenia and Slovakia.

[6]The names of the banks included in the sample are reported in Table A.1. Only 31 banks out of the 103 banks included in our sample have a coverage of 20 years or more.

[7]For the final year in the sample there are less banks available given reporting delays.

[8]Table A.4 reports the definitions and sources of the banking variables included in the dataset.

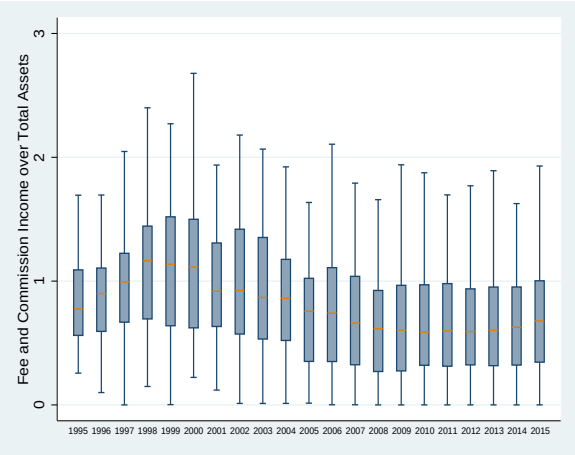
[9]Table A.5 reports the definitions and sources of the macroeconomic and financial variables included in the dataset.

[10]Stiroh (2004) shows that the share of non-interest income over net operating revenue (i.e. net interest income plus non-interest income) increased from 25% in 1984 to 43% in 2001 for US commercial banks. ECB (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.

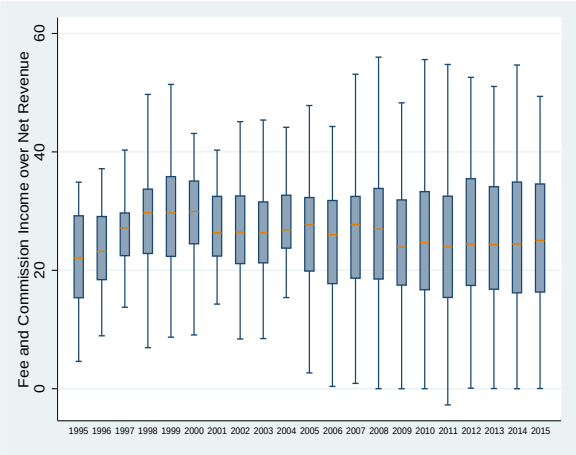
to total income for a sample of euro area significant banking groups has hovered between 20% and 25% in the last years. ECB (2013a) confirms this range but stresses that there is a large heterogeneity across euro area countries. In some countries like Finland, France and Italy, the share of fee and commission income over net income reaches levels of around 30%, whereas in countries like Greece or Ireland this ratio is closer to 15%.

As shown in Figure 1, we observe a similar pattern of fees and commissions in our sample.

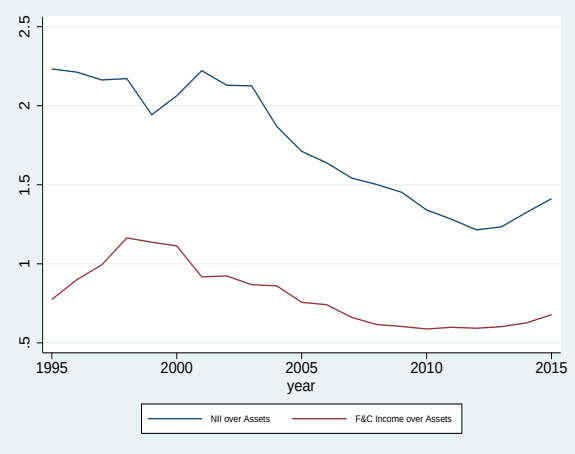
Figure 1: Dynamics of fee and commission income ratios and net interest income ratios for the banks in the sample between 1995 and 2015.



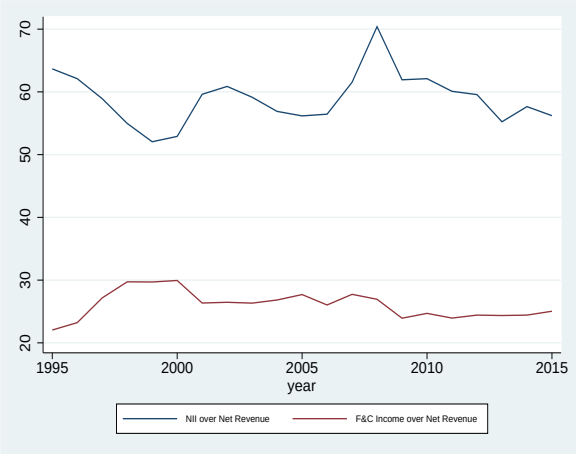
(a) Fee and commission income over total assets



(b) Fee and commission income over net revenue



(c) Median net interest income and fees and commission over total assets



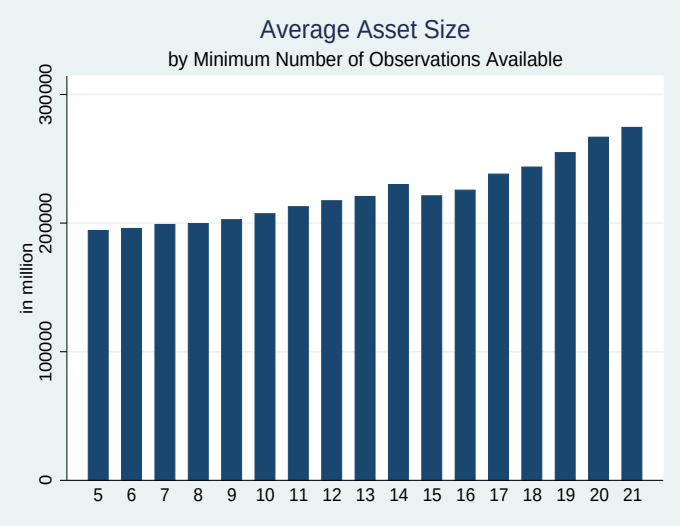
(d) Median net interest income and fees and commission over net revenue

Plot (a) shows that, in the last two decades, the median ratio of fee and commission income over total assets hovered between 0.6% and 1.2%.[11] Moreover, plot (b) shows that the median

[11] Differences with respect to the previous studies are due to the fact that we use gross rather than net fee and commission income and that we employ a somewhat different sample of banks as well as a different time period.

ratio of fees and commissions over net revenue remained rather stable between 22% and 30%. Although this ratio is only half of that of net interest income over net revenue, it still indicates that fees and commissions are an important source of revenues for European banks. We also observe differences across countries. While this ratio lies between 20% and 30% for the bulk of the 19 countries in our sample, there are few countries either somewhat below the 20% mark (Belgium, Ireland, Malta, Netherlands) or above the 30% mark (Estonia, Italy, Latvia, Slovenia). Furthermore, plot (c) compares the evolution of fee and commission income over assets with that of net interest income over assets in our sample and shows that the former ratio has overall remained rather stable over the considered time period while the latter ratio has significantly decreased as a result of the general decline of the level of interest rates over the past decade and in light of the financial crisis. Only recently, net interest income has picked up again in a somewhat more benign financial environment. Moreover, it is also of interest to compare the evolution of fees and commission income over net revenue with that of net interest income over net revenue. As we can observe from plot (d), the median share of fees and commissions over net revenue, while relatively stable, has increased over the early years of our sample to peak around 2000. It then decreased slightly, but it still remains at a higher level than it was in the beginning of the sample period. In contrast, the share of net interest income has exhibited more variation over time.

Figure 2: Average asset size by number of observations available, in million euro



Finally, in Figure 2, banks are grouped according to their number of available observations and the mean asset size for each group of banks is shown. The minimum number of observations available is five, while the maximum number of observations available is 21 observations. Notably, the average asset size is about 40% larger for the last group of banks than for the first group of banks (€274 billion compared to €194 billion, respectively). This finding indicates

that banks with a larger coverage in terms of observations in our sample are also larger banks. To take this fact into account we employ the ratio of fee and commission income to total assets for our empirical analysis.

4 Variable Selection: the Least Angle Regression procedure

As also suggested by some earlier studies surveyed in Section 1, there is a large set of candidate factors that may be associated with developments in the ratio of fee and commission income to total assets. In order to examine which variables are the most relevant in influencing fee and commission income over assets, we apply a variable selection procedure. More precisely, in the presence of many candidate variables, the objective is to choose as regressors those variables that have the most explanatory power for our variable of interest, while keeping the model relatively sparse to avoid over-fitting problems.

For the purpose of variable selection, we employ the Least Angle Regression (LARS) algorithm as developed by Efron et al. (2004) that can be seen as a generalization of the Least Absolute Shrinkage and Selection Operator (LASSO) by Tibshirani (1996) and Foreward Stagewise Linear Regression (henceforth Stagewise), which is employed by Kapinos and Mitnik (2016) in a stress testing context. The LASSO and Stagewise are constrained versions of the LARS algorithm.[12]

The LASSO is a shrinkage and selection method for linear regressions which minimizes the residual sum of squares while imposing a bound on the sum of the absolute regression coefficients in the model thereby shrinking some coefficients towards zero. Stagewise follows a similar approach. However, in this case, the regression function is built successively. More precisely, the procedure starts with all the coefficients being at zero and then with small steps ϵ moves in the direction of the most correlated variables with the respective residual at each step.

The LARS approach, which derives its name from the underlying geometry, is also a stepwise procedure that implies equiangular movements towards a predictor variable which is as highly correlated with the residual as are the other variables already used in the prediction.[13] To perform variable selection, Efron et al. (2004) suggest making use of Mallow's C_p statistic, a standard information criterion, which is often used as a stopping rule in a model selection context. The algorithm developed by the authors is computationally efficient as it only requires as many computational steps (linear regressions) as are candidate variables available.

[12] As explained by Efron et al. (2004) the LARS algorithm can also be employed to compute either a LASSO or a Stagewise solution. The results are very similar for these three approaches.

[13] The LARS procedure also starts with the coefficients being zero and then increases the coefficient of the most highly correlated predictor x_1 until the residual from the prediction is as highly correlated with a second predictor x_2. At this point the algorithm proceeds, in contrast to the Stagewise procedure, in a direction equiangular between x_1 and x_2 until a third variables x_3 is as highly correlated with the residual. Once more the algorithm moves in equiangular fashion towards these three predictors until a fourth variable x_4 exhibits as high correlation with the residual and so on.

As explained above, the LARS algorithm allows selecting a subset of regressors from a predetermined larger set of variables and provides an order of inclusion reflecting the importance of each independent variable in explaining the variable of interest. In this analysis, the initial set of variables, to which the LARS algorithm is applied, comprises lagged fee and commission income over assets and both the contemporaneous value and the first lag of those macro-financial variables which are available for the scenario analysis, namely: stock market returns, the CPI inflation rate, real GDP growth, the first difference of the short-term rate, the first difference of the long-term rate and residential property price inflation. This set of variables is consistent with economic rationale and in line with the main factors discussed in the related literature. While arguably also variables related to banks' financial market activity, such as brokerage and M&A financing could be relevant, in the model presented in this paper we rely on macro-financial factors as these are the variables which are typically included in stress test scenarios. Therefore, our variable set is largely determined by the list of variables available in the macro-financial scenarios used in the 2016 EU-wide stress test.

Table 1 shows the results from our variable selection procedure. More specifically, Table 1 provides the order of inclusion, the C_p statistic at each step for the resulting model as well as the R-square implied by the individual LARS models. Indeed, Efron et al. (2004) suggest selecting the set of variables as implied by the minimum value of the C_p statistic.

Table 1: LARS variables selection

Step	C_p	*R-square*	*Variable*
1	10835.05	0	
2	114.57	0.8984	F&C income over assets (t-1)
3	60.22	0.9031	Δ Short term rate(t-1)
4	62.08	0.9031	Stock market returns(t-1)
5	20.41	0.9068	Stock market returns
6	15.22	0.9074	Δ Long term rate(t-1)
7	14.66	0.9076	Res. property price growth
8	6.39*	0.9085	Real GDP growth
9	8.05	0.9085	Inflation rate(t-1)
10	9.91	0.9085	Δ Short term rate
11	11.41	0.9086	Δ Long term rate
12	11.43	0.9087	Res. property price growth(t-1)
13	13.03	0.9088	Real GDP growth(t-1)
14	14.00	0.9088	Inflation rate

The table shows results based on the LARS variable selection algorithm. At each step of the procedure the C_p statistic, the *R-squared* of the model and the newly included variable is provided. The model with the minimum C_p value is marked with *.

The model implied by the minimum C_p statistic includes seven out of the thirteen candidate variables. The variable set selected by the LARS approach comprises in decreasing order of inclusion: the lag of the fee and commission income to assets ratio, the lag of the first difference of the short-term interest rate, stock market returns (both the lag and the contemporaneous

value), the lag of the first difference of the long-term interest rate, real GDP growth and residential property price inflation. These seven variables are included as regressors in our benchmark model.

5 Empirical strategy and results

In the following section, we first present the econometric methods used to estimate the relationship between the fee and commission income ratio to assets and the set of variables identified by the application of the LARS and then we report and comment the regression results. Finally, we perform a sequence of robustness checks to assess the stability and reliability of the results.

5.1 Econometric framework

Fee and commission income, like other sources of income, is driven both by the macro-financial environment and by bank-specific characteristics. However, the aim of this analysis is to shed more light on the relationship between the variables identified by the application of the LARS and the fee and commission income to asset variable for the banks in our sample.[14] To conduct this study, we apply different panel econometric methods. First, we use a FGLS estimator corrected for heteroskedasticity to estimate the following model:

$$y_{i,t} = \phi y_{i,t-1} + \mathbf{X}_t \beta + \epsilon_{i,t} \tag{1}$$

where $y_{i,t}$ is the variable of interest (i.e. fee and commission income to total assets) for each individual bank i at time t. Fee and commission income is scaled by total assets to account for the different size of banks in the sample. The relative average stability and persistency[15] of the fee and commission income-to-total asset ratio over time suggests that the lag of the ratio might be a strong predictor of its contemporaneous value. Therefore, equation 1 features as explanatory factor $y_{i,t-1}$, i.e. the lagged dependent variable. Finally, $\mathbf{X}_t$ is a $[1xj]$ vector and represents the j explanatory variables[16] selected applying the LARS and $\epsilon_{i,t}$ is the zero-mean bank-specific error term.

In the second econometric approach, we estimate a fixed effects (FE) model to account for bank-specific unobserved factors that might drive individual banks results. Estimating a FE

[14] This investigation focuses particularly on the role played by macroeconomic and financial factors as these variables are generally included in macroeconomic scenarios used for stress test purposes. However, bank-specific factors are also considered as part of our robustness analysis.

[15] In this context, a unit root hypothesis can be rejected. Results based on Fisher-type tests (Augmented Dickey-Fuller and Phillips-Perron) are available from the authors upon request.

[16] As we employ a European sample, where differences in the macroeconomic environment of individual countries exist, we use country-specific macro variables. However, a possible caveat of this approach is the fact that banks are exposed not only to the domestic economy, but through foreign operations also to macroeconomic conditions elsewhere. It could thus be worthwhile to construct bank-specific macroeconomic indicators reflecting each bank's exposure to other countries; although data availability prevents us from pursuing this approach.

model implies assuming the existence of time-invariant bank-specific effects that are potentially correlated with the individual regressors unlike in a random-effects model. In this context, we estimate the following equation:

$$y_{i,t} = \alpha_i + \phi y_{i,t-1} + \mathbf{X}_t\beta + \epsilon_{i,t} \tag{2}$$

where α_i are the bank-specific fixed effects. The inclusion of a lagged dependent variable in a panel framework might yield biased and inconsistent estimates due to the correlation between the lagged dependent variables and the error terms (Nickell 1981) and (Kiviet 1995), so called dynamic panel bias. To address this issue, we make use of two other estimation strategies. First, as shown in equation 3, we employ a system GMM estimator (Blundell and Bond 1998) that combines the original equation in levels and an equation in differences

$$\begin{aligned} y_{i,t} &= \alpha_i + \phi y_{i,t-1} + \mathbf{X}_t\beta + \epsilon_{i,t} \\ \Delta y_{i,t} &= \phi \Delta y_{i,t-1} + \Delta \mathbf{X}_t\beta + \Delta\epsilon_{i,t} \end{aligned} \tag{3}$$

This estimator is designed for estimating models with a dynamic regressor and with independent variables that are not strictly exogenous. However, dynamic panel data models which use GMM estimators (Arellano and Bond 1991; Arellano and Bover 1995; Blundell and Bond 1998) are unfortunately only asymptotically efficient and have poor finite sample properties particularly when the size of the sample is small.

Finally, we use, as our preferred estimation strategy, an LSDVC estimator as developed by Kiviet (1995) and extended upon by Bun and Kiviet (2003) and Bruno (2005a) and Bruno (2005b) which allows for the inclusion of a lagged endogenous variable, see equation (2). The LSDVC estimator is our preferred method as it not only corrects for dynamic panel bias, but it is also potentially more efficient than the GMM estimator[17], and it allows for the explicit estimation of bank-specific fixed effects. However, it is relevant to highlight that the LSDVC estimator is designed for estimating models with strictly exogenous independent variables. We employ this approach as implemented by Bruno (2005b), i.e. initialising the bias correction with the Blundell-Bond (system GMM) estimator.[18] To ensure that the estimated asymptotic standard errors of the LSDVC estimator yield reliable t-statistics, statistical inference for the coefficients is based on bootstrapped standard errors (50 iterations) (Bruno 2005b).

5.2 Regression results

Our analysis has two main objectives: first, it aims at examining in more depth the relationship between the fee and commission income ratio and the set of variables identified by the application

[17] As shown by Kiviet (1995), Judson and Owen (1999) and Bun and Kiviet (2003), who investigated the biases introduced by different dynamic panel estimators using Monte Carlo experiments.

[18] As discussed by Bun and Kiviet (2003) and Bruno (2005b), the choice of initial estimator has only a marginal impact on the final results.

of the LARS; second, it strives to develop a model that can be used for scenario analysis in a stress testing context. In this regard, the estimated parameters can be used to project the fee and commission income ratio into the future taking as input the macroeconomic projections from a specific scenario.

Table 2 shows the regression results based on the variable set selected by the LARS: the lag of the fee and commission income to assets ratio, the lag of the first difference of the short-term interest rate, stock market returns (both the lag and the contemporaneous value), the lag of the first difference of the long-term interest rate, real GDP growth and residential property price inflation. More specifically, Table 2 depicts the results for the four different econometric approaches discussed in Section 5.1. The first column shows the estimated coefficients for the FGLS model while the second column depicts the results for the FE approach. Finally, column (*3*) shows the system GMM results and column (*4*) exhibits the results based on the LSDVC estimator.

The models generally yield qualitatively similar results. In particular, the latter three models imply both similar coefficients and significance levels.[19] More precisely, for these three models the selected macro-financial variables which are significant comprise the lag of the first difference of the short-term rate, stock market returns and real GDP growth. Moreover, the explanatory variables display the expected signs when significant. The lag of the fee and commission income ratio exhibits a positive coefficient (with an estimated value ranging from 0.67 in the FE model to 0.81 in the LSDVC model) as expected given the high positive autocorrelation of the dependent variable. Also, as expected, real GDP growth and stock market returns are positively associated with the fee and commission income to total asset ratio. Their increases, respectively, indicate a better performing real economy and growing financial markets which would both imply an expansion of those financial services (e.g. M&A and securities brokerage) that generate fee and commission income. This finding is in line with the previous literature and thus corroborates with results reported by Coffinet et al. (2009) for real GDP growth and stock market returns and by Lehmann and Manz (2006) and Hirtle et al. (2014) for stock market returns. The estimated coefficient on the (lagged) first difference of the short-term rate has a significant negative sign. This result can be justified by the following mechanism: lower short-term rates are usually associated with higher bank business volumes, which should have a positive effect on fee and commission income. At the same time, it may also reflect a rebalancing effect whereby a bank changes its focus from activities generating net interest income towards more fee and commission income-generating activities. Covas et al. (2014) also find a qualitatively similar result.

The scale of the estimated coefficients can be interpreted in the following way: one additional percentage point of real GDP growth would lead, ceteris paribus, to an increase in the average fee and commission income ratio to total assets of about 1% given an average fee and commission income ratio in our sample of 0.79%.

[19] In this context, it is worth underlining that the FGLS model neither includes individual fixed effects nor addresses the possible dynamic panel bias.

Table 2: Regressions for fee and commission income over assets on the selected macroeconomic and financial variables

	(1) FGLS	(2) FE	(3) GMM	(4) LSDVC
F&C Income/Total Assets(t-1)	0.9801***	0.6666***	0.8066***	0.8122***
	(175.59)	(7.23)	(9.29)	(34.22)
Δ Short term rate(t-1)	-0.0103***	-0.0174***	-0.0180***	-0.0199***
	(-4.81)	(-4.17)	(-4.79)	(-4.49)
Stock market returns(t-1)	0.0003***	0.0003	0.0003	0.0003
	(2.72)	(1.22)	(1.34)	(1.14)
Stock market returns	0.0003***	0.0005**	0.0005**	0.0006***
	(2.98)	(2.43)	(1.98)	(2.60)
Δ Long term rate(t-1)	-0.0039*	0.0018	-0.0009	0.0006
	(-1.91)	(0.43)	(-0.22)	(0.19)
Real GDP growth	0.0012	0.0085**	0.0053*	0.0087***
	(1.08)	(2.38)	(1.77)	(3.30)
Res property price growth	-0.0016***	0.0021	-0.0008	0.0005
	(-3.68)	(1.40)	(-0.64)	(0.38)
Constant	0.0044	0.2255***	0.1277**	
	(1.27)	(3.37)	(2.01)	
Observations	1119	1119	1119	1119
Banks	103	103	103	103
Wald χ^2	31671***		299***	1463***
F-statistic		75***		
AR(2) Arellano-Bond test (p-value)			0.27	
Hansen J test (p-value)			0.11	
Number of instruments			10	

***, **, and * denote significance at the 1%, 5% and 10% level, respectively. Parameter estimates based on the feasible GLS approach (FGLS), equation 1, the fixed effects approach (FE) and the LSDVC approach (LSDVC), both equation 2, and system GMM (GMM), equation 3, are shown. z-statistics (t-statistic in the FE case) based on heteroscedasticity and autocorrelation robust standard errors are shown in parenthesis. Below the parameter estimates the number of observations and the number of individual banking groups in the sample are provided. Further, the Wald χ^2 statistic (F-statistic in the case of FE model) to test for the joint significance of the estimated parameters is given. Finally, for the GMM approach the p-value based on the Arellano-Bond statistic to test for second-order autocorrelation and on the Hansen J statistic to test the validity of the overidentifying restrictions, respectively, is shown. Further, in this case the lagged dependent variable is instrumented with its own lags (collapsed), the exogenous variables in the model and the time dummies.

The test results included for the GMM approach indicate the validity of the instruments used, as the over-identifying restrictions are fulfilled, and further show the absence of second-order autocorrelation in the residuals when using this estimator.[20]

[20]Results for the FGLS model stand out in yielding a much higher autocorrelation coefficient of 0.98. This can be explained by the absence of any fixed effects in the model. In this model also the other macro-financial variables have significant coefficients (in particular lagged stock market returns and residential property price growth), while the coefficient on real GDP growth is not significant. Given the before mentioned caveats of this model, we deem these results less reliable.

5.3 Robustness checks

We perform a sequence of robustness checks to ensure the stability and reliability of the results of our preferred model which relies on the LSDVC estimator; the results of which are shown in Table 3.

Table 3: Robustness regressions for the LSDVC model

	(*1*)	(*2*)	(*3*)	(*4*)
F&C Income/Total Assets(t-1)	0.8025***	0.8104***	0.8064***	0.9102***
	(40.24)	(33.27)	(32.65)	(43.70)
Δ Short term rate(t-1)	-0.0136***	-0.0196***	-0.0206***	-0.0174***
	(-3.56)	(-4.50)	(-4.38)	(-3.44)
Stock market returns(t-1)		0.0002	0.0003	0.0004
		(1.06)	(1.11)	(1.57)
Stock market returns	0.0006***	0.0006***	0.0006***	0.0005*
	(2.80)	(2.64)	(2.59)	(1.82)
Δ Long term rate(t-1)		-0.0003	0.0000	0.0012
		(-0.10)	(0.00)	(0.35)
Real GDP growth	0.0103***	0.0086***	0.0091***	0.0064**
	(6.27)	(3.26)	(3.37)	(2.32)
Res property price growth		0.0004	0.0003	-0.0005
		(0.34)	(0.27)	(-0.40)
Inflation rate		0.0027		
		(0.84)		
Inflation rate(t-1)			0.0030	
			(0.78)	
Observations	1207	1119	1119	729
Banks	103	103	103	53
Wald	1760***	1516***	1373***	2476***

***, **, and * denote significance at the 1%, 5% and 10% level, respectively. Parameter estimates for equation 2 based on the LSDVC approach are shown. z-statistics based on heteroskedasticity and autocorrelation robust standard errors are shown in parenthesis. Below the parameter estimates, the number of observations and the number of individual banking groups in the sample are provided. Further, the Wald χ^2 statistic to test for the joint significance of the estimated parameters is given.

We begin with removing those variables that are insignificant in the LSDVC model. In particular, these are lagged stock market returns, the lag of the first difference of the long-term interest rate and residential property price inflation. The results shown in column (*1*) confirm the robustness of the results which are hardly changed in terms of the significance and the value of coefficients of those variables left in the model. A further robustness check consists of including additional control variables in the LSDVC benchmark model. More specifically, we enhance the model with either the lag or the contemporaneous value of CPI inflation, as the variable is the only that has not been picked in either form by the LARS algorithm. As shown in columns (*2*) and (*3*) in Table 3, the main results of the analysis are robust to the inclusion of these additional controls. Indeed, the variables, which were included in the benchmark model in

line with the results of the LARS, maintain their significance and sign. Also both the coefficient on lag and on the contemporaneous value of inflation are insignificant in their respective models. Therefore, there does not seem to be an omitted variable bias problem in the LSDVC model as far as these variables are concerned.[21]

Finally, we test the robustness of our benchmark results by limiting the sample to only those banks with a value of total assets larger than or equal to 50 billion which roughly halves the sample. As shown, in column (*4*) in Table 3, the main results of the analysis do not change on a qualitative basis. The main difference consists of a somewhat higher autocorrelation coefficient and slightly smaller coefficients on the macro-financial variables with the coefficient on stock market returns being on a lower significance level.

6 Scenario analysis

In this section, a scenario analysis of fee and commission income over total assets under both a baseline and an adverse scenario for a three-year horizon between end-2015 and end-2018 for 18 euro area countries is conducted.[22]

The projections of fee and commission income over total assets are computed feeding the macroeconomic scenarios through the estimated benchmark LSDVC model (presented in column (*4*) in Table 2) which is seeded with the end-2015 bank-level data. It is worth highlighting that bank specific fee and commission income projections are aggregated and displayed at country level. First, the model projections are computed at bank level year by year and, then, country level projections are generated as weighted averages of the bank level projections.

The scenarios adopted in this exercise are those employed in the 2016 EU-wide stress test exercise coordinated by the EBA and were published in February 2016. The baseline scenario is based on an extension of the European Commission (EC) Autumn 2015 forecast, while the adverse scenario reflects a joint scenario of a reversal in global risk premia, weak financial market profitability in a low growth environment, rising public and private debt sustainability concerns and shocks to the shadow banking sector. For the euro area as a whole these shocks result in real GDP growth rates falling below the baseline rate by 2.8, 3.2 and 1.1 percentage points, respectively in 2016, 2017 and 2018. More information on the scenarios and the developments of the key macroeconomic and financial variables under the baseline and the adverse macroeconomic scenarios are reported in EC (2016) and ESRB (2016) .

In this context, it is key to emphasize that the exercise presented in this section is not a

[21] We also assessed the impact of including in the estimated model bank-specific variables reflecting on the bank business model, namely the retail ratio and the leverage ratio. In both cases, the coefficients of the benchmark variables did not change substantially such that there does not seem to be an omitted variable bias problem related to these indicators. It is worth noting that the estimated coefficient for the retail ratio is positive and significant. This seems to suggest that more traditional banks on average have a higher fee and commission income to total assets ratio. The coefficient on the leverage ratio is negative and significant indicating that more leveraged banks on average have lower fee and comission income. Results are available upon request.

[22] No projections for Lithuania are included, as there are no data points for fee and commission income for the respective banks at the end of the sample, i.e. for 2014 and 2015.

Figure 3: Projection of fee and commission income over assets aggregated at country level, % change with respect to the cut-off level

sensitivity analysis but a proper stress testing analysis. More specifically, this analysis studies how consistent changes in all the relevant explanatory macroeconomic and financial factors included in the benchmark model affect fee and commission income over the stress test horizon.

However, it is also important to note some limitations of the approach. First, potential feedback effects between the banking sector and the real economy are not taken into account. Second, total assets (used to compute the fee and commission income ratio) are not explicitly

Figure 3: Projection of fee and commission income over assets aggregated at country level, % change with respect to the cut-off level, cont.

modelled as they are assumed to be constant over the stress test horizon.[23] Third, even though our model results seem robust to the different specifications discussed before, some open questions on model coefficient stability remain. In particular, the economic literature has emphasized the importance of financial cycles for the conduct of macro-prudential policy, because the financial system might evolve differently as a response to such policy during booms and busts

[23]However, the assumption of constant total assets is in line with the static balance sheet approach used in the 2011 EBA stress test, the 2014 ECB Comprehensive Assessment stress test and the 2016 EU-wide stress test.

Figure 3: Projection of fee and commission income over assets aggregated at country level, % change with respect to the cut-off level, cont.

(Hiebert, Schüler and Peltonen 2015; Rünstler and Vlekke 2016; Stremmel 2015). Similarly, income elasticities might be different across financial cycles which would suggest that fee and commission income could react differently to some financial and/or macroeconomic variables under a baseline versus an adverse scenario. To the extent that this source of income would react relatively stronger (weaker) to the relevant variables in a crisis scenario, the severity of the corresponding projections would be amplified (reduced) relative to what is shown in this

section. This would further imply that elasticities might differ across countries, e.g. between crisis and non-crisis countries. However, given the data limitations, we leave this important topic for future research.

Figure 3 displays the projections of fee and commission income ratios aggregated at country level for 18 euro area countries in terms of percentage changes with respect to the cut-off levels. The light blue bars are the projected percentage changes under the baseline scenario while the dark blue bars are the projected percentage changes under the adverse scenario. In the Appendix, figure A.4 shows the aggregated country level projections of fee and commission income ratios in levels. The light gray line in each graph shows the actual historical value, the light blue line represents the baseline scenario projection and the dark blue line represents the adverse scenario projection.

The figures show that fee and commission income projections are sensitive to the different macroeconomic developments. As expected, the projections of fee and commission income under the adverse scenario are consistently below the projected income under the baseline scenario. On average, the cumulative deviation between the adverse and baseline country level projections over the stress test horizon corresponds to 55 basis points (bps) of the 2015 CET1 ratio.[24] For the majority of countries, the projected fee and commission income ratios feature an overall decline under the adverse scenario with respect to the 2015 starting level. An exception to that are Cyprus, Spain and Slovenia which end up with a somewhat higher fee and commission income ratio at the end of the scenario horizon. This can be explained by the combination of a milder scenario for these countries and positive fixed effects for the relevant banks.

For the majority of the remaining countries, namely Finland, Austria, Belgium, Finland, France, Greece, Italy, Luxembourg, Portugal and Slovakia, the adverse scenario projections follows rather a V-shaped path, i.e. they first decline but then they bounce back towards their starting level, but typically not fully. This reflects the specific characteristics of the scenario which features first a decline in economic indicators followed by a subsequent recovery. For the other countries examined in this exercise, the projections exhibit a continuous reduction in fee and commission income. Overall, the countries most severely affected under the adverse scenario in terms of the decline in fee and commission income ratio would be Belgium, Finland, Ireland, Luxembourg and Malta. These countries would see their projection ratios decrease by more than 20%.

By contrast, baseline projections, in most cases, exhibit either a rather steady or an increasing path with respect to the 2015 cut-off level. Only the projections for Belgium, Germany, Estonia, Finland, Ireland and Malta feature declines of more than 5% under the baseline scenario.

Figure A.5 also reports the decomposition of the contribution of the explanatory factors to

[24] In particular, the cumulative deviation between the adverse and baseline country level projections over the stress test horizon is 43 bps for Austria, 71 bps for Belgium, 24 bps for Cyprus, 64 bps for Germany, 67 bps for Estonia, 38 bps for Spain, 90 bps for Finland, 51 bps for France, 48 bps for Greece, 50 bps for Ireland, 35 bps for Italy, 69 bps for Luxembourg, 83 bps for Latvia, 51 bps for Malta, 67 bps for the Netherlands, 40 bps for Portugal, 33 bps for Slovenia and 58 bps for Slovakia.

the average adverse-baseline deviation of banks' fee and commission income over the stress test horizon. The figure shows that in the first year of the stress test horizon real GDP growth and the stock market returns are the largest contributors to the deviation. In the second year and particularly in the third year, the role of these two factors declines due to the increasing effect of the lag term of the dependent variable.

Overall, these findings point to the potential for seriously misrepresenting the sensitivity of fee and commission income to macro-financial shocks when conducting bank stress tests where this material income item is treated as independent from the macro scenario. Hence, explicitly modelling fee and commission income as advertised in this study appears to be a promising approach for future bank stress tests.

7 Conclusions

In this paper, we present an empirical macro-financial model for the estimation of fee and commission income (as a ratio of total assets) for a broad sample of euro area banks.

In particular, in this analysis, we first employ a variable-selection technique (LARS) to determine the set of relevant regressors for our variable of interest.

Then, using different panel econometric techniques, we find that fee and commission income over assets is varying with the economic and financial cycle. Specifically, it is significantly related to real GDP growth, the lag of the short-term interest rate, stock market returns and its own lag. These results are qualitatively consistent across all the econometric approaches applied.

Finally, as a last step of our study, we conduct a scenario analysis. We use the estimated parameters to project fee and commission income over assets over a three-year horizon conditional on both a baseline and an adverse financial and macroeconomic scenario. This scenario analysis illustrates how fees and commissions are sensitive to the different macroeconomic developments. The resulting fee and commission projections aggregated at country level are considerably more conservative under the adverse scenario than under the baseline scenario. Moreover, for the majority of the countries, the projected fee and commission income ratios feature an overall decline with respect to the cut-off level under the adverse scenario.

These findings suggest that stress tests assuming scenario-independent fee and commission income projections are likely to be flawed. According to the results presented in this paper, it is plausible that fee and commission income will differ depending on the macro-financial environment and, ignoring this, presumably would lead to a misrepresentation of banking-sector soundness and resilience to shocks.

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Appendix

Table A.1: Sample of banks

No.	*Name*	*Country*	*Number of observations*	*First observation*	*Last observation*
1	BAWAG P.S.K.	AT	13	2003	2015
2	Erste Group Bank	AT	21	1995	2015
3	RZB Österreich	AT	16	2000	2015
4	RLB NÖ-Wien	AT	8	2008	2015
5	RLB-OÖ	AT	11	1997	2015
6	Argenta Group	BE	8	2008	2015
7	AXA Bank Europe	BE	6	2008	2013
8	Belfius Banque, S.A.	BE	10	2006	2015
9	Dexia NV	BE	21	1995	2015
10	KBC Group NV	BE	21	1995	2015
11	Bank of Cyprus	CY	21	1995	2015
12	Hellenic Bank Public Company Ltd	CY	21	1995	2015
13	Aareal Bank AG	DE	15	2001	2015
14	Bayerische Landesbank	DE	17	1999	2015
15	Commerzbank AG	DE	21	1995	2015
16	DekaBank Deutsche Girozentrale	DE	17	1999	2015
17	Deutsche Apotheker - und Ärztebank EG	DE	11	2005	2015
18	Deutsche Bank AG	DE	21	1995	2015
19	DZ Bank AG Dt. Zentral-Genossenschaftsbank	DE	11	2005	2015
20	Hamburger Sparkasse AG	DE	9	2007	2015
21	HSH Nordbank AG	DE	14	2002	2015
22	Landesbank Baden-Württemberg	DE	14	2002	2015
23	Landesbank Berlin AG	DE	20	1995	2014
24	Landesbank Hessen-Thüringen GZ	DE	15	2001	2015
25	Landeskreditbank Baden-Württemberg - Förderbank	DE	9	2006	2014
26	Landwirtschaftliche Rentenbank	DE	11	1999	2015
27	Mnchener Hypothekenbank eG	DE	9	2007	2015
28	Norddeutsche Landesbank -GZ-	DE	14	2002	2015
29	NRW.BANK	DE	21	1995	2015
30	SEB AG	DE	6	2008	2014
31	VW Financial Services AG	DE	13	2003	2015
32	WGZ Bank AG Westdt. Geno. Zentralbank, Ddf	DE	16	1999	2015
33	SEB Pank	EE	11	1995	2014
34	ABANCA Corporacion Bancaria, S.A.	ES	6	2010	2015
35	Banco Bilbao Vizcaya Argentaria, S.A.	ES	21	1995	2015
36	Banco de Sabadell, S.A.	ES	19	1997	2015
37	Banco Mare Nostrum, S.A.	ES	5	2011	2015
38	Banco Popular Español, S.A.	ES	21	1995	2015
39	Banco Santander, S.A.	ES	21	1995	2015
40	Bankinter, S.A.	ES	21	1995	2015
41	Banco Financiero y de Ahorros, S.A.U.	ES	6	2010	2015
42	Ibercaja - Caja de Ahorros y Monte de Piedad de Zaragoza	ES	5	2008	2012
43	Criteria Caixa, S.A.	ES	15	1999	2013
44	Fundacion Bancaria Unicaja	ES	16	1999	2014
45	Liberbank, S.A.	ES	5	2011	2015
46	Danske Bank Oyj	FI	8	2008	2015
47	Nordea Bank Finland Plc	FI	7	2009	2015
48	OP Cooperative	FI	17	1995	2015

Table A.1: Sample of banks, cont.

No.	*Name*	*Country*	*Number of observations*	*First observation*	*Last observation*
49	BNP Paribas	FR	21	1995	2015
50	BPCE SA	FR	7	2009	2015
51	BPI Groupe S.A.	FR	10	2006	2015
52	Groupe Credit Agricole	FR	14	2002	2015
53	Confederation Nationale du Credit Mutuel	FR	16	1999	2014
54	HSBC France SA	FR	11	1995	2014
55	La Banque Postale	FR	10	2006	2015
56	RCI Banque SA	FR	12	2003	2015
57	Societe de financement local	FR	6	2008	2014
58	Societe Generale	FR	21	1995	2015
59	Alpha Bank, S.A.	GR	21	1995	2015
60	Eurobank Ergasias, S.A.	GR	18	1998	2015
61	National Bank of Greece, S.A.	GR	21	1995	2015
62	Piraeus Bank, S.A.	GR	21	1995	2015
63	Allied Irish Bank	IE	21	1995	2015
64	The Governor and Company of the Bank of Ireland	IE	6	2010	2015
65	Permanent TSB Group Holdings plc	IE	6	2009	2014
66	Ulster Bank Ireland	IE	9	2007	2015
67	Gruppo Carige	IT	21	1995	2015
68	Gruppo Monte dei Paschi di Siena	IT	20	1996	2015
69	Gruppo Banca Popolare dell'Emilia Romagna	IT	21	1995	2015
70	Gruppo BPM - Banca Popolare di Milano	IT	21	1995	2015
71	Banca Popolare di Sondrio	IT	21	1995	2015
72	Gruppo Bancario Banca Popolare di Vicenza	IT	10	2006	2015
73	Gruppo Banco Popolare	IT	10	2006	2015
74	CREDITO EMILIANO SPA	IT	19	1997	2015
75	Gruppo Bancario ICCREA	IT	9	2007	2015
76	Gruppo Bancario Intesa Sanpaolo	IT	21	1995	2015
77	Gruppo Bancario Mediobanca	IT	21	1995	2015
78	Gruppo UBI Banca	IT	14	2002	2015
79	Gruppo UniCredit	IT	21	1995	2015
80	Gruppo Bancario Veneto Banca	IT	9	2007	2015
81	DNB Bankas	LT	7	2002	2008
82	NORD/ LB Lietuva	LT	7	2002	2008
83	Banque et Caisse d'Epargne	LU	13	2000	2015
84	Banque internationale a Luxembourg	LU	9	1995	2015
85	ABLV Bank AS	LV	7	2009	2015
86	Latvijas Unibanka	LV	13	1995	2015
87	Swedbank AS (Latvia)	LV	7	2009	2015
88	Bank of Valletta p.l.c.	MT	14	1999	2015
89	HSBC Bank Malta p.l.c.	MT	14	2002	2015
90	ABN Amro Group N.V.	NL	11	2005	2015
91	BNG Bank	NL	14	2002	2015
92	Coperatieve Centrale Raiffeisen-Boerenleenbank B.A.	NL	21	1995	2015
93	ING Group N.V.	NL	9	2007	2015
94	Royal Bank of Scotland N.V.	NL	6	2009	2014
95	SNS Bank NV	NL	16	2000	2015
96	Banco BPI, S.A.	PT	21	1995	2015
97	Banco Comercial Portugus, S.A.	PT	21	1995	2015
98	Caixa Geral de Depsitos, S.A.	PT	12	2004	2015
99	Nova Kreditna Banka Maribor	SI	16	1999	2015
100	Nova Ljubljanska banka d.d.	SI	9	2001	2015
101	Slovenska sporitelna A.S.	SK	11	1995	2015
102	Tatra banka	SK	18	1998	2015
103	Vseobecna uverova banka, A. S.	SK	21	1995	2015

Table A.2: Number of banks in the sample by country

Country	Number of banks
Austria	5
Belgium	5
Cyprus	2
Estonia	1
Finland	3
France	10
Germany	20
Greece	4
Ireland	4
Italy	14
Luxembourg	2
Latvia	3
Lithuania	2
Malta	2
Netherlands	6
Portugal	3
Slovenia	2
Slovakia	3
Spain	12
Total	103

Table A.3: Number of banks in the sample by year

Year	Number of banks
1995	36
1996	37
1997	40
1998	41
1999	48
2000	47
2001	49
2002	58
2003	61
2004	59
2005	63
2006	71
2007	78
2008	86
2009	94
2010	98
2011	100
2012	99
2013	100
2014	98
2015	88
Total	1451

Table A.4: Definition and sources of the banking variables in the dataset

Variables	Definitions	Source
Fee and commission income	Commissions & fees earned; It includes commissions and fees. earned from service charges, loan servicing fees, brokerage fees, and trust fees and management fees.	Bloomberg
Assets	Sum of cash & bank balances, fed funds sold & resale agreements, investments for trade and sale, net loans, investments held to maturity, net fixed assets, other assets, customers' acceptances and liabilities	Bloomberg

Table A.5: Definition and sources of the macroeconomic and financial variables in the dataset

Variables	Definitions	Source
GDP growth	Annual growth rate of gross domestic product at market price, chain linked volumes	ECB SDW
Inflation rate	Harmonised Index of Consumer Prices	ECB SDW
House prices	Residential property prices	ECB SDW
Short-term interest rate	Money market rate	ECB SDW
Long-term interest rate	10y government bond yield	ECB SDW
Stock market index	National stock market index	ECB SDW

Table A.6: Summary statistics

Variables	Obs.	Mean (in %)	Std. Dev.	Min	Max
FC Income/Total Assets	1451	0.79	0.53	0.00	4.35
Stock market returns	2014	8.85	33.52	-73.57	641.78
Real GDP growth	2034	1.90	3.16	-14.81	26.28
Inflation rate	2031	2.01	2.27	-13.95	14.51
Δ Short term rate	1918	-0.33	1.39	-9.24	10.81
Δ Long term rate	1902	-0.36	1.25	-13.98	9.58
Res property price growth	1752	3.54	7.78	-38.01	52.22

Figure A.4: Projection of fee and commission income over assets aggregated at country level

Figure A.4: Projection of fee and commission income over assets aggregated at country level, cont.

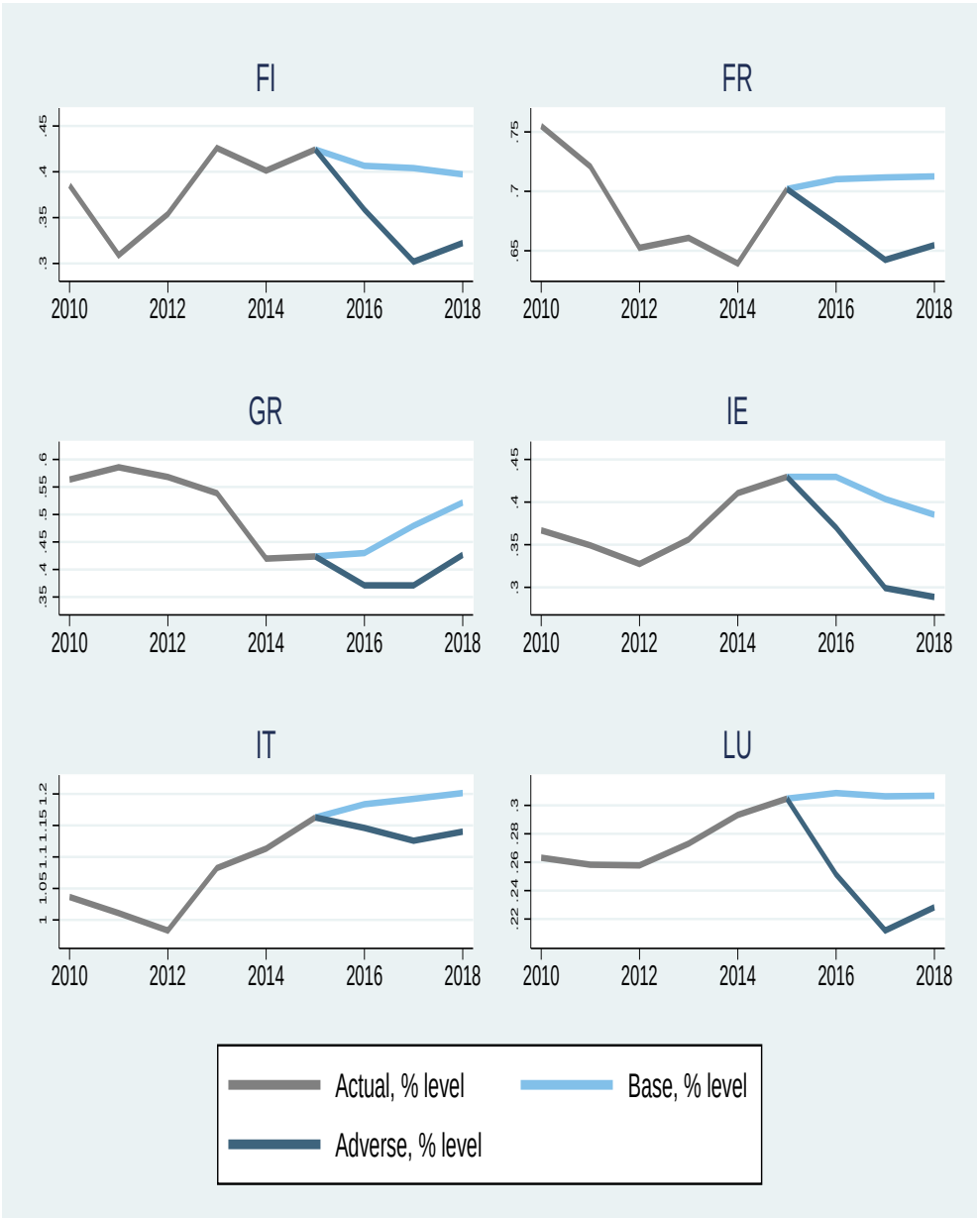
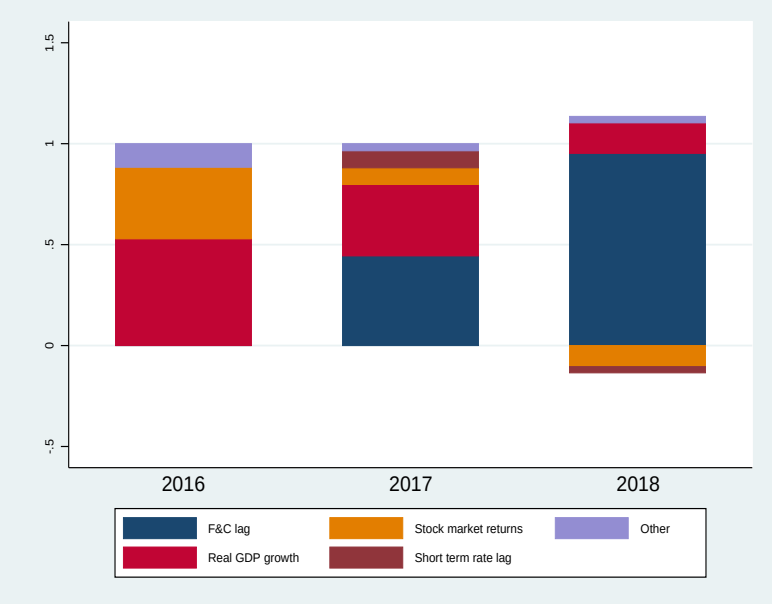


Figure A.4: Projection of fee and commission income over assets aggregated at country level, cont.

Figure A.5: Decomposition of the contribution of the explanatory factors to the average adverse-baseline deviation of banks' fee and commission income.



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