Master in Economics and Finance

Finance Programme

Scenario bias under IFRS 9 standards

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ABSTRACT IN ENGLISH:

IFRS 9, which changes the estimation of Loan Loss Provisions from an Incurred Loss model to an Expected Credit Loss model, entered into application in 2018. It changed the focus to a forward-looking perspective, which requires banks to do macroeconomic forecasts. However, banks have incentives to bias those forecasts in order to undertake earnings or capital management. For this thesis, I collect the forecasts of the 184 European listed banks from their annual reports and I conclude that they do capital management but not earnings management. The sample is small, but results hold after robustness checks and the residuals satisfy OLS assumptions.

ABSTRACT IN SPANISH

En 2018 se hizo efectivo el estándar IFRS 9. Con él, la estimación de las Provisiones por Pérdidas Crediticias pasaba de un modelo de Pérdida Incurrida (Incurred Loss) a un modelo de Pérdida Esperada (Expected Credit Loss). Esto implica un enfoque prospectivo, de manera que los bancos tienen que efectuar previsiones macroeconómicas. Sin embargo, estos tienen incentivos para sesgar sus previsiones y así alterar sus ingresos o capital. Para esta tesis, recolecto las previsiones macroeconómicas de los 184 bancos cotizados de Europa a partir de sus memorias anuales, y concluyo que usan sus previsiones para alterar el capital, pero no los ingresos. La muestra es pequeña, pero los resultados superan tests de robustez y los residuos satisfacen las asunciones de OLS.

KEYWORDS IN ENGLISH:

IFRS 9, Capital Management, Earnings Management, Scenario Bias

KEYWORDS IN SPANISH:

IFRS 9, Manipulación de Capital, Manipulación de Ingresos, Sesgo de Previsiones

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Abstract

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Keywords: IFRS 9, capital management, earnings management, scenario bias.

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1 Acknowledgements

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2 Introduction

The accounting standard IFRS 9 (on financial instruments) entered into application in 2018. This new standard changes the estimation of Loan Loss Provisions (LLP): It goes from an Incurred Loss (IL) model to an Expected Credit Loss (ECL) model. This change was motivated by the outcome of the IL model during the 2008 financial crisis, as it was criticized to provision *too little, too late* (Abad & Suarez (2018)). While the IL model was focused on the past and updated provisions after trigger events, the ECL model has a forward-looking perspective, and therefore it is based in future forecasts. As López-Espinosa et al. (2021) observe, ECL Loan Loss Provisions have been more predictive of future bank risk than IL provisions, which confirms its forward-looking success. However, the ECL model is criticized to be even more procyclical than the IL model (Borio (2019)), which implies an excess credit supply during good times and too little during bad times.

Concretely, banks have to compute the Probability of Default of a loan (or group of loans) and the respective Loss Given Default. Therefore, under the Expected Credit Loss (ECL) model, future macroeconomic forecasts are a key ingredient of this, and IFRS 9 allows firms to compute them on their own. Moreover, firms can also choose the macroeconomic variables used, the number of macroeconomic scenarios and the weights assigned to them, which generates a great degree of discretion, which makes earnings management and capital management easier compared to the IC model.

The objective of IFRS 9 is to establish principles for the financial reporting of financial assets so that they present relevant and useful information to the users of financial statements, in a way that facilitates the assessment of the amounts, timing and uncertainty of future cash flows[1]. Therefore, with this in mind, they require firms to[2]

- Compute an unbiased amount of Expected Credit Losses (ECL)
- Disclose information about the macroeconomic forecasts that were used

Banks have incentives to manage earnings and capital through provisions, and Loan Loss provisions are a major element of them (Beatty & Liao (2014)). Therefore, it is possible that banks use their discretion in computing ECL to bias it in their favour. Moreover, we find that approximately two thirds of European listed banks, which have to comply with IFRS 9, do not disclose their macroeconomic forecasts. This may be related simply to their resources to comply (proxied by bank size), but could also be an indicator of ECL manipulation.

Nevertheless, computing banks' bias is not straightforward, and there is no database with the information of whether banks disclose their forecasts or not and what are the forecasted values. For this reason, I have collected this information from the Annual reports of the 184 European listed banks for the period from 2018 to 2020.

This thesis will consist in a literature review, followed by a theoretical discussion of the prior literature problems and the solution that using the forecasting bias offers, followed by a explanation of the data collection process with a description of that data, and finally followed by the results and conclusions. In the results I will first analyse the disclosing decision by banks, then the provided forecasted values, and finally I will conduct some robustness checks and residuals' analyses.

3 Literature review

There is plenty of literature regarding earnings and capital management, and about whether banks tend to manipulate Loan Loss Provisions to that end. This thesis contributes to the literature by analysing it in the new framework of IFRS 9 and, especially, by using forecasting bias as a proxy for discretional LLP. To my knowledge, this has never been done before and it solves some endogeneity issues that prior literature had.

[1] IFRS 9 standard, paragraph 1.1
[2] IFRS 9 standard, paragraph 5.5.17

Following Wall & Koch (2000), I will start by doing a more qualitative analysis of the incentives that banks have to manage their capital and earnings. To begin with, if financial markets were efficient in the strong form (Fama (1970)) – that is, prices reflect all public and private information – managers would have no incentive to distort their financial accounts. That is because, in that situation, regulators and investors would only need to look at price data to value the bank, and prices would not be affected by financial account manipulation.

However, one requirement for financial markets to be strong form efficient is that the marginal cost of acquiring and analysing information must be zero, but it turns out that this is not the case. As Degeorge et al. (1999) show, all humans use thresholds when evaluating information, which in the case of earnings are: Zero earnings, last year earnings, and stock analysts' earnings expectations. Accordingly, Barth et al. (1999) show that firms that sustain yearly increases in earnings have a higher Price-Earnings ratio, which drops dramatically the year that that firm fails to increase earnings once again.

All these thresholds together generate income smoothing incentives for firms, because when they are below a threshold they will want to increase earnings (artificially if necessary) to meet it. In the case that they are above the thresholds, they may want to manipulate the income account downwards, generating a cookie jar of hidden reserves, in case they may need them in the future.

In addition, there is also a third more extreme case, the Occasional Big Bath (Kirschenheiter & Melumad (2002)), in which firms are in such a desperate situation that they decide to reduce income even more in order to make the following year easier. Nevertheless, the rarity of this situation in banks makes it difficult to test this hypothesis, and papers about it are less frequent.

Regarding capital management, incentives come from the minimum capital ratios required by the Basel accords. The mechanism through which provisions affect capital is the following: There are two accounts affected by LLP in a bank's Capital, which are Retained Earnings and Loan Loss Allowances. For each new euro of LLP, Retained Earnings decrease by $(1-\tau)$, where τ is the corporate tax rate. Loan Loss Allowances are the aggregation of current and previous LLP. Therefore, for each new euro of LLP, LLA increase by 1. Consequently, the net effect is $1 - (1 - \tau) = \tau$, which is positive.

However, the Basel accords, in 1988, made it more complex by separating capital into Tier 1 and Tier 2 capital. Tier 1 is the highest quality capital, and includes Retained Earnings, while Loan Loss Allowances belong to Tier 2 capital and only up to a limit of 1.25% of Risk Weighted Assets. Consequently, in this setting, an increase of LLP reduces Tier 1 capital by 1, but increases total capital by τ. Since Basel requires ratios on both measures, the capital management incentives are more situational. Incentives by Tier 1 capital are that, the lower the T1 capital, the less provisions you want to have. On the other hand, incentives by total capital are that, the lower the capital, the more provisions you want to have. According to (Beatty and Liao 2014), Tier 1 capital incentives seem to dominate.

With respect to the empirical literature, Beatty & Liao (2014) provide an extensive literature review. They analyse two different periods: Pre-Basel and Post-Basel. They find that most papers find a negative correlation between LLP and capital before Basel (Moyer (1990), Collins et al. (1995), Beatty (1995)), but that there is less consensus on earnings management. However, this period suffers from small samples due to lack of data availability.

In the Post-Basel period, Ahmed et al. (1999) fins a positive correlation with tier 1 capital but no earnings management. Kim & Kross (1998) finds that low-capital banks reduced their provisions levels after the Basel regulation change.

Turning into newer research, Norden & Stoian (2013) finds that there is earnings management in banks' Loan Loss Provisions, Leventis et al. (2011) finds earnings management but not capital management in European Banks and Curcio & Hasan (2015) does not find any discretionary use of LLP in Euro Area banks.

In conclusion, as Beatty & Liao (2014) point out, there are heterogeneous results in the literature. As they suggest, it is probably due to the fact that there is no consensus on what model to use, and therefore each paper counts with different assumptions which lead to different results.

4 Theoretical discussion and research question

One of the main critiques that can be done to the earnings and capital management literature of LLP relies on the ability to successfully separate discretionary provisions from non-discretionary provisions. Non-discretionary provisions are the legitimate level of LLP, that is, the value that regulators would expect to see and that reflects the Expected Credit Loss from financial assets. On the other hand, discretionary provisions are everything that deviates from that, and therefore respond to other illegitimate incentives, like earnings and capital management.

Therefore, every specification that incorrectly identifies part of the non-discretionary component as the discretionary one is potentially endogenous, since the non-discretionary component is likely to be correlated with earnings or capital.

To the end of separating both components, two main types of strategies have been used in the literature. One consists in to run a regression of PLL on relevant credit risk variables, and consider the residuals as discretionary LLP (take Chang et al. (2011) for an example), while the other simply consists in using these relevant credit risk variables as controls.

Nevertheless, the failure to identify all relevant variables can result again in omitted variable bias, in the case that unidentified control variables are correlated both with LLP and revenues or capital. Moreover, if revenues or capital were determining factors of non-discretionary provisions, none of these methods would be able to deal with the resulting endogeneity, since they would identify a legitimate correlation as earnings or capital management.

Consequently, we need a proxy for non-discretionary provisions that is independent of everything else, in other words, we need an exogenous variable. The fact that with IFRS 9 banks have to disclose their macroeconomic forecasts provides us an excellent exogenous determinant of LLP: Macroeconomic forecasts' bias.

Of course, macroeconomic forecasts are very related to revenues. However, what we will try to identify is its bias. For bias we understand the systematic differences with what would be the "real" unbiased forecast. Accordingly, we can model the Unbiased Macroeconomic Forecast of bank b, period t and country c (UMF_{btc}) as the "real" unbiased expectation plus the following random errors:

- Optimism shared by all banks (B) in all observations: α^B
- Optimism shared by all banks in year t: α_t^B
- Optimism shared by all banks about country c: α_c^B
- Optimism shared by all the forecasts of the same bank b: α_b^B
- An observation-specific random error: ϵ_{btc}^B

$$UMF_{btc} = \alpha^B + Unbiased_{ct} + \alpha_t^B + \alpha_c^B + \alpha_b^B + \epsilon_{btc}^B$$

In the case that banks were biased, we should add a time-bank specific bias term, which is a linear combination of other variables X, like earnings and capital. Therefore, the Biased Macroeconomic Forecast of bank b, period t and country c (BMF_{btc}) would be:

$$BMF_{btc} = \alpha^B + Unbiased_{tc} + Bias_{bt} + \alpha_t^B + \alpha_c^B + \alpha_b^B + \epsilon_{btc}^B$$

$$Bias_{bt} := \beta X_{bt}$$

Moreover, we can also model the macroeconomic forecast of an Independent Institution (II), which is assumed to be unbiased, as the "real" unbiased forecast of country c at time t, plus the following random errors:

- Constant optimism level of the II in all observations: α^{II}
- Optimism of the II about country c, constant in all time periods: α_c^{II}
- Optimism of the II in year t, constant in all countries: α_t^{II}
- An observation-specific random error: ϵ_{ct}^{II}

$$UMF_{tc}^{II} = \alpha^{II} + Unbiased_{tc} + \alpha_t^{II} + \alpha_c^{II} + \epsilon_{btc}^{II}$$

Consequently, if we take the difference between the banks' forecasts and the II's forecasts as our bias measure, we obtain:

$$Diff_{btc} = (\alpha^B - \alpha^{II}) + Bias_{bt} + (\alpha_t^B - \alpha_t^{II}) + (\alpha_c^B - \alpha_c^{II}) + \alpha_b^B + (\epsilon_{btc}^B - \epsilon_{btc}^{II})$$

However, if one of those error terms was correlated with some of the Xs, we would be obtaining wrong estimates for the betas. Nevertheless, as we can appreciate, $(\alpha_t^B - \alpha_t^{II})$ is constant within time periods, $(\alpha_c^B - \alpha_c^{II})$ is constant within countries, and α_b^B is constant within banks. Therefore:

- In case we believe that $(\alpha_t^B - \alpha_t^{II}) \neq 0$ and it is correlated with one of the Xs, we would need to use time Fixed Effects (FE). For example, if the years with higher average bank revenue the II tended to be more optimistic or pessimistic than banks.
- In case we believe that $(\alpha_c^B - \alpha_c^{II}) \neq 0$ and it is correlated with one of the Xs, we would need to use country FE. For example, if banks of a certain country with higher average revenues ratio tend to be more optimistic about their country than the II.
- In case we believe that $\alpha_b^B \neq 0$ and it is correlated with one of the Xs, we would need to use bank FE. This would happen if banks with a higher average revenue ratio are consistently more optimistic about macroeconomic perspectives than the II, regardless of the revenues of a certain period. Since I will only use one country per bank (its domestic country), bank FE implies country FE.

Consequently, if we use both Bank Fixed Effects, we would only be analysing the variation within banks, that is, when a bank sees a revenues or capital increase in its accounts, how much does it alter its optimism. Moreover, if we add Time FE, we would be controlling for generalized optimism of the II or all banks in a certain period.

In addition, the variance of ϵ_{cbt}^B and ϵ_{ct}^{II} depend on the c or t. That is because some countries or years may be more difficult to predict. For example, forecasts in 2020 have more variance than those done in 2019 or 2018. This generates the need to use heteroskedasticity robust errors. Moreover, the residuals of each observation may be correlated at the bank level. For that reason, we should use clustered standard errors at the bank level.

In the light of the above, my research question is whether banks manipulate their macroeconomic forecasts following earnings and capital management incentives, which is against what IFRS 9 mandates. I assume that banks and the II use the same information when forecasting the economy. Therefore, if banks were not biased, the difference between the II and banks (banks' optimism) should be an exogenous random variable, independent from capital and revenues.

Given that two thirds of the sample have not disclosed their forecasts, we can do two different analyses: One regarding the decision of whether to disclose or not, and the other regarding the value of disclosed forecasts. Since the first analysis suffers from the endogeneity issue mentioned above, it will be just a descriptive analysis of correlations. This analysis however will help to interpret the second one, which does not have endogeneity issues but uses a non-random sample, which is the banks that chose to disclose the forecasts.

5 Data collection and description

5.1 Data collection process

There is no database with information about the forecasts used by banks. Therefore, I have collected it directly from the annual reports of the banks. The sample consists in the 184 European listed banks during the period of 2018 to 2020. Since at the moment of the data collection not all banks had published the annual report of 2020, for that year we only have 87 banks. Since the dataset has a more generic purpose than this thesis, I collected:

- Whether the bank discloses the forecasts (Disclose = 2), they don't disclose them but mention their ECL methodology (Disclose = 1), or they do not even mention IFRS 9 (Disclose = 0), which would suggest that we wrongly put them in the sample or that we took the wrong document as Annual Report.
- The number of scenarios used by each bank.
- The weights associated to those scenarios.
- The variables and countries forecasted, for each one of the scenarios.

- In case they disclosed the forecasted values, those were also included, jointly with the:
  - Time horizon of that forecast. Sometimes the banks provided point-in-time estimates for multiple years, and sometimes they computed an average over a time horizon.
  - Specification of that variable. For example, the GDP variable can be real or nominal, and the inflation variable can use different price indices.

From this, we can already appreciate that there are multiple ways to define a bank's bias. One of the issues resides in that each forecast is defined by its country, its concrete specification of the variable and its time horizon. Therefore, we find that there is a great heterogeneity of forecasts that cannot be compared one another.

Consequently, when choosing the unbiased forecast to compare them with, we cannot use the average of forecasts with the same characteristics, since there are very few observations that belong to a concrete set of characteristics. Seen in another way, the problem is that there are too many possible permutations of characteristics.

Another better option would be to compare the forecasts to an Independent Institution that provides forecasts for all the possible permutations of characteristics. Fortunately, the IMF provides this for all the countries in the world, and is the one that we will be using.

The next issue resides in the fact that most banks have different forecasted variables or countries for each bank-year pair. However, we are not interested in seeing whether a certain forecast is biased, but in seeing whether a certain bank-year pair is biased. Therefore, we face a trade-off between dropping information and assuming a way to aggregate all that information.

Assuming how to best aggregate the information is problematic. The most straightforward way to do it would be to compute the average of biases, but this assumes that all variables and countries have the same importance. For example, if a bank wants to manipulate its forecasts, it is more likely that it will do it to its domestic country ones, instead of others that will have a smaller impact on the estimated ECL. Consequently, it is more informative to analyse individually a type of forecasts, instead of analysing an average of them.

5.2 Data description

In tables 1 and 2 I provide summary statistics of the financial accounts of my sample. There we can appreciate that most variables are not complete, which reduces my sample size for some regressions.

Table 1: Summary statistics of financial accounts data in COMPUSTAT

Statistic	N	Mean	St. Dev.	Min	Median	Max
Total Assets	528	167,319.800	447,813.200	9.800	14,197.300	3,023,683.000
Total Capital	319	14,321.950	29,266.630	49.500	2,145.800	184,423.000
Tier 1 Capital	314	12,422.700	25,131.280	47.900	1,996.600	160,173.000
Tier 2 Capital	274	2,370.495	4,720.868	0.000	232.200	26,096.000
Total Revenues	398	3,919.945	8,991.691	−629.400	522.815	53,342.000
Revenue Before Loan Losses	441	4,084.532	9,756.628	−951.400	537.060	61,103.280
Provision For Loan Losses	410	544.152	1,504.654	−321.990	37.170	15,044.960
Total Loans	329	95,880.930	184,693.600	71.000	15,221.900	959,700.000

555 observations, composed by 184 banks during 3 years
Data in millions of Euros

Table 2: Summary statistics of standardized values

Statistic	N	Mean	St. Dev.	Min	Median	Max
LLP	271	0.015	0.033	−0.020	0.004	0.239
Revenues BLL	439	0.054	0.120	−0.013	0.028	1.155
T1Cap	314	0.079	0.031	0.025	0.073	0.235
T2Cap	274	0.009	0.007	0.000	0.008	0.044
Capital	319	0.087	0.032	0.028	0.082	0.235
Loans	321	6.266	32.355	0.021	0.573	476.222

LLP standardized by total loans
Rest of variables standardized by total assets

Moreover, as we can appreciate in table 3, since GDP and unemployment are the variables that have been forecasted by a larger number of banks, these are the ones that I will individually analyse. House prices is the third most important variable, probably due to the mortgage exposure of my sample.

In addition, in figures 1 and 2 we can see that the unemployment forecasts of the IMF and banks tend to be similar in terms of mean, and therefore the difference has mean zero.

Table 3: Main variables forecasted in each bank-year pair

Variable	Frequency
GDP	124
Unemployment	96
House prices	64
Interest rates	20
Inflation	8

However, it appears that, for some reason, banks are generally more pessimistic about GDP than the IMF.

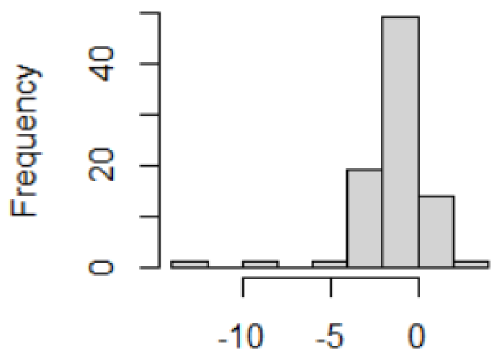


Figure 1: Histogram of GDP optimism (percentage points)

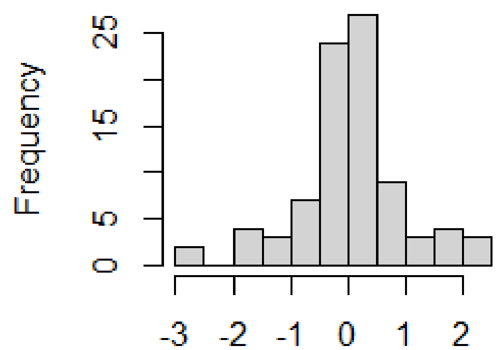


Figure 2: Unemployment optimism (percentage points)

In table 4 we observe that more than half of the listed European banks are not disclosing their forecasts, even though this number is decreasing. Table 5 gives us a closer look at the disclosure transition of banks, and there we can observe a ratchet effect. That is, when banks start disclosing they can't go back.

Table 4: Evolution of the disclosure status

	2018	2019	2020
0	14	15	8
1	125	105	54
2	45	60	25

In table 6 we observe that the preferred number of scenarios is 3, although some banks use more than that. Given that the scenarios that are not the baseline usually have different

Table 5: Transition matrix of disclosure status

	0	1	2
0	14	0	0
1	0	105	17
2	1	0	43

2018 (left) to 2019

	0	1	2
0	7	0	0
1	1	54	5
2	0	0	20

2019 to 2020

weights associated, for this thesis I will only be using the forecasts of the baseline scenario, which is also always the one with the highest weight. In table 7 we observe that there is also heterogeneity in the symmetry of weights, although banks have been moving towards asymmetric weights, which may indicate an increase in sophistication.

Table 6: Number of scenarios

	2018	2019	2020
3	65	93	31
4	4	10	2
5	13	8	3
Other	2	3	3

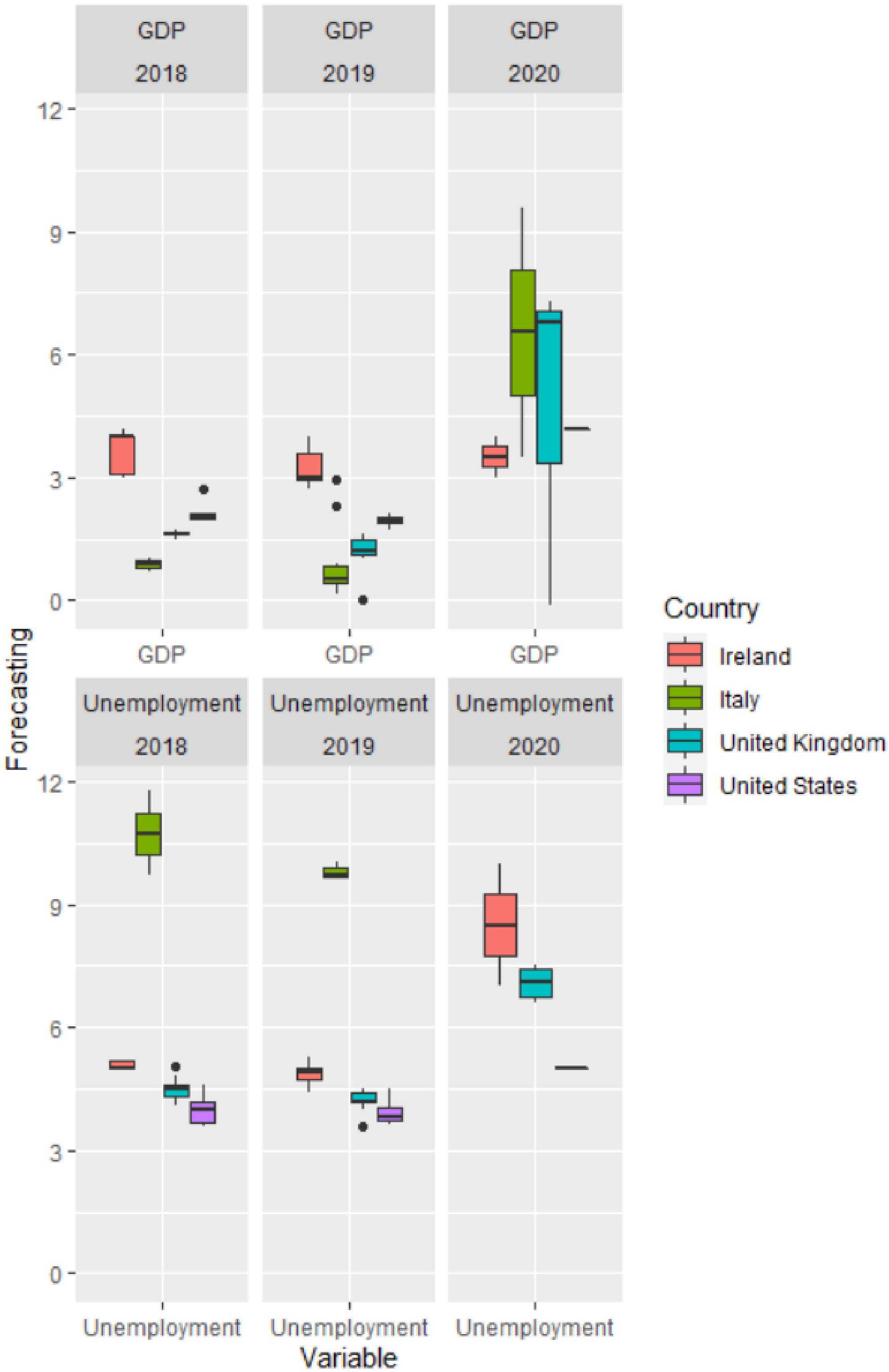
Table 7: Symmetric scenario weights

	2018	2019	2020
No	42	72	11
Yes	65	67	23

Finally, in figure 3 we have an overview of the different baseline forecasts for the most forecasted countries. There we can also appreciate the big heterogeneity in forecasts, specially in the most unpredictable years, like 2020, and in the variables with the highest value, which also have a higher standard deviation.

In conclusion, all these degrees of discretion make it difficult for regulators to ensure that banks are using the adequate level of Loan Loss Provisions. We will be able to analyse the baseline scenario forecast for the domestic country, but there are many more variables and decision that come into play.

Figure 3: Boxplot of forecasted values



6 Results

6.1 Analysis on the disclosing decision

For the following tables, I am using the variables summarized in table 2, that is, the standardized variables.

As said above, first we are going to analyse the decision of whether to disclose the forecasts or not, and after that we are going to analyse the disclosed forecast values.

As we can appreciate in table 5, banks seem to experience a ratchet effect in their disclosing decision. We see that, when a bank decides to disclose the forecasts, it never goes back to not disclosing them in the following years. Therefore, it is important to consider this when doing the regression, since banks that are already disclosing do not really have a decision to make.

Therefore, we are going to run two regressions in table 8, one for 2018, when every bank still had to take the decision, and another for 2019, but omitting the banks that had already disclosed in 2018. For robustness sake, I will do the same but using a Logistic Model apart from a Linear Probability Model. Since banks with Disclose = 0 (which means that they do not mention their ECL estimation methodology nor even IFRS 9) were probably mistakenly included in the sample or we took the wrong document as Annual Report, I will omit them from the sample.

We can observe that, as expected, banks with higher resources (proxied by Assets) are more likely to comply with regulation. However, this effect dissapears the following year, suggesting that size is a relevant factor the first year of the regulation, but that for the banks that did not disclose their results on 2018, it stops being relevant. In addition, it also appears that, controlling for Assets, banks with a higher revenues ratio are less likely to disclose their forecasts, although this effect is not so significant in the logistic model. This appears to be counter-intuitive, and may be related to earnings management, unless we suffer from ommited variable bias. If it was the case of earnings management, it would imply that banks with higher revenues, which have the incentive to increase provisions and bias their forecasts downwards, are the ones that have the higher incentives to bias and, consequently, avoid disclosing their forecasts.

In any case, this allows us to have an idea of the sample that we are going to use in the Optimism tables. Concretely, it tells us that our sample will have higher assets than average and a lower revenues ratio than average.

Table 8: The disclosing decision

	Dependent variable:			
	Disclose			
	Linear Probability Model		*Logistic Model*	
Year	2018	2019	2018	2019
	(1)	(2)	(3)	(4)
log(Assets)	0.072***	0.054	0.349***	0.301
	(0.023)	(0.034)	(0.130)	(0.218)
Capital	3.270*	−0.102	17.725*	2.281
	(1.697)	(1.561)	(9.178)	(11.921)
Revenues BLL	−1.948**	−0.538	−12.675*	−10.361
	(0.861)	(0.873)	(7.187)	(11.204)
Constant	0.385***	0.466***	−0.579	−0.022
	(0.134)	(0.164)	(0.629)	(0.822)
Observations	109	65	109	65
R^2	0.086	0.075		
Adjusted R^2	0.060	0.029		
Log Likelihood			−65.398	−32.569
Akaike Inf. Crit.			138.795	73.138
Residual Std. Error	0.464 (df = 105)	0.418 (df = 61)		
F Statistic	3.296** (df = 3; 105)	1.643 (df = 3; 61)		

Note: *p<0.1; **p<0.05; ***p<0.01

Heteroskedasticity consistent errors used in all regressions

Banks that mention the ECL computation method but do not disclose the forecasts (Disclose = 0), against banks that disclose them (Disclose = 1). The first and third regression contain all the sample of the year 2018, whereas the second and fourth only contain those banks of 2019 that had not disclosed in 2018.

However, when we analyse whether the banks that disclose have higher or lower Loan Loss Provisions (LLP) in table 9, we can appreciate that the decision to disclose their forecasts does not translate into higher or lower LLP for our sample. If the earnings management hypothesis previously stated was true (that banks with higher revenues do not disclose for earnings management reasons) we would expect to see a significant negative coefficient on *Disclose*. Moreover, the rest of variables are not meant to provide causal inference, but to serve as controls for *Disclose*, since in table 8 we have seen that they are related to *Disclose*, and they may be related to *LLP*.

Table 9: Relation of disclosing with LLP

	Dependent variable:	
	LLP	
Year	2018	2019
	(1)	(2)
log(Assets)	0.002	0.002
	(0.001)	(0.002)
Capital	−0.003	0.183
	(0.086)	(0.136)
Revenues_BLL	0.214	0.174
	(0.261)	(0.308)
Disclose	−0.004	−0.006
	(0.005)	(0.004)
Constant	0.012	0.0001
	(0.008)	(0.009)
Observations	83	46
R^2	0.109	0.181
Adjusted R^2	0.064	0.101
Residual Std. Error	0.026 (df = 78)	0.032 (df = 41)
F Statistic	2.394* (df = 4; 78)	2.258* (df = 4; 41)

Note: *p<0.1; **p<0.05; ***p<0.01
Heteroskedasticity consistent errors used in all regressions
Same samples as previous table

6.2 Analysis on the forecasted values

I am going to analyse both the forecasts of GDP and unemployment for the domestic country of the banks. All tables will include heteroskedasticity consistent errors clustered at the bank level, and I am going to do all the regressions without Fixed Effects (FE), with only time FE, and with time and bank FE. Recall that, assuming that banks and the IMF use the same information to forecast, their difference in forecasts should be an exogenous random variable.

In general, however, we must be very cautious, as the sample is small. For this reason I will afterwards undertake robustness analyses and analyses of the residuals. In spite of that, for comparability, I will restrict the unemployment sample to those observations that are both in the GDP and unemployment sample, which does not reduce the sample much. Moreover, considering the time-bank Fixed Effects the most important regression, I will also restrict the sample to those banks that have at least two observations, which is the sample that Fixed Effects uses.

As we can appreciate in table 10, it appears that the optimism in GDP is truly exogenous, but that the optimism in unemployment, when controlling for bank and time FE, is not. Concretely, we can observe that is has a strong positive relation with capital, and also a positive relation with revenues.

The positive relation with capital goes in line with the incentive of total (T1 + T2) capital management, in opposition to Tier 1 capital management. This implies that banks with lower capital want to increase their provisions, and to that end they bias downwards their forecasts. To check robustness and that indeed this is the dominant incentive, we will run a regression separating capital into T1 and T2 in table 11.

Regarding the coefficient on revenues, it is contrary to what earnings management incentives would indicate. I have two hypothesis about why this happens. The first is that, contrary to my assumption, banks and the IMF do not use the same information when forecasting. Concretely, banks are influenced by their own earnings, which makes them be more optimistic than the IMF. The second hypothesis is that, due to the small sample, this estimate is just not robust.

When we run the same regression but separating capital into T1 and T2 in table 11, we confirm that the total capital incentive (which moves in the T2 capital direction) dominates. Not only this, but we also find very significant coefficients of T2Cap in the GDP regression. In addition, it seems that the positive revenues effect is robust to this new specification.

Table 10: Forecasting bias

	Dependent variable:					
	Optimism in GDP			Optimism in unemployment		
	(1)	(2)	(3)	(4)	(5)	(6)
Revenues BLL	−25.132	−24.661	122.490*	22.248	14.659	70.607**
	(20.987)	(21.093)	(70.049)	(20.238)	(19.712)	(34.963)
Capital	5.369	5.484	−15.646	5.378	9.541	42.562***
	(8.089)	(8.360)	(30.121)	(11.794)	(12.265)	(14.198)
Constant	−1.050			−1.021		
	(0.735)			(0.758)		
Observations	50	50	50	50	50	50
Banks	21	21	21	21	21	21
R^2	0.032	0.030	0.154	0.091	0.114	0.474
Adjusted R^2	−0.009	−0.056	−0.659	0.052	0.036	−0.031
Time FE	No	Yes	Yes	No	Yes	Yes
Bank FE	No	No	Yes	No	No	Yes

Note: *p<0.1; **p<0.05; ***p<0.01
Heteroskedasticity consistent errors clustered at the bank level in all regressions

Table 11: Forecasting bias, separating capital into T1 and T2

	Dependent variable:					
	Optimism in GDP			Optimism in unemployment		
	(1)	(2)	(3)	(4)	(5)	(6)
Revenues BLL	−22.041	−23.585	79.146	35.167**	28.218**	85.345**
	(14.772)	(15.429)	(71.977)	(15.283)	(12.785)	(34.445)
T1Cap	2.480	3.681	−25.478	−12.772	−8.269	26.012*
	(9.284)	(8.978)	(45.115)	(12.035)	(10.148)	(13.596)
T2Cap	66.578***	67.822***	43.040	−10.539	11.919	73.657**
	(12.905)	(16.531)	(46.844)	(35.236)	(30.003)	(34.279)
Constant	−1.614**			−0.069		
	(0.675)			(1.062)		
Observations	40	40	40	40	40	40
Banks	17	17	17	17	17	17
R^2	0.123	0.123	0.129	0.084	0.096	0.583
Adjusted R^2	0.050	−0.006	−0.888	0.008	−0.037	0.096
Time FE	No	Yes	Yes	No	Yes	Yes
Bank FE	No	No	Yes	No	No	Yes

Note: *p<0.1; **p<0.05; ***p<0.01

Heteroskedasticity consistent errors clustered at the bank level in all regressions

Finally, in table 12 we can check that, indeed, optimism in the forecasts has a negative effect on Loan Loss Provisions. Again, here the rest of variables are not meant to have a causal interpretation. They just serve as controls for Optimism, since we know that they are correlated with optimism and they are also probably correlated with LLP.

Table 12: Effect of optimism on LLP

	Dependent variable:					
	Loan Loss Provisions (LLP)					
	(1)	(2)	(3)	(4)	(5)	(6)
Revenues_BLL	1.467	1.777	−0.167	1.014	1.031	−0.287
	(1.352)	(1.342)	(0.165)	(1.169)	(0.877)	(0.295)
Capital	−0.590	−0.621	−0.135**	−0.589	−0.665*	−0.065
	(0.458)	(0.440)	(0.060)	(0.432)	(0.398)	(0.084)
Optimism in GDP	0.0005	0.002	−0.002***			
	(0.005)	(0.005)	(0.0004)			
Optimism in unemployment				0.009	0.020**	−0.002**
				(0.008)	(0.010)	(0.001)
log(Assets)	0.008	0.009	−0.018***	0.006	0.007*	−0.020***
	(0.006)	(0.006)	(0.003)	(0.005)	(0.004)	(0.005)
Constant	0.043			0.051		
	(0.032)			(0.034)		
Observations	30	30	30	30	30	30
Banks	13	13	13	13	13	13
R^2	0.316	0.367	0.581	0.360	0.519	0.438
Adjusted R^2	0.206	0.202	−0.104	0.258	0.393	−0.481
Time FE	No	Yes	Yes	No	Yes	Yes
Bank FE	No	No	Yes	No	No	Yes

Note: *p<0.1; **p<0.05; ***p<0.01
Heteroskedasticity consistent errors clustered at the bank level in all regressions

6.3 Robustness and residuals analysis

Finally, the small size of the sample requires a robustness and residuals analysis.

We will start by checking the OLS assumption that the error term is normally distributed, which is important to correctly estimate the confidence intervals of the coefficients. In the case of large samples this is not relevant, since the Central Limit Theorem also applies for the coefficients. However, as said, our sample is not large.

Nevertheless, when we plot the histogram of residuals in figures 4 and 5 we can see that, both for GDP and unemployment optimism, they resemble a normal distribution. In addition, from a more formal perspective, all three typical normality tests (Shapiro-Wilk, Jarque-Bera and D'Agostino-Pearson tests) fail to reject normality with big p-values (table 13).

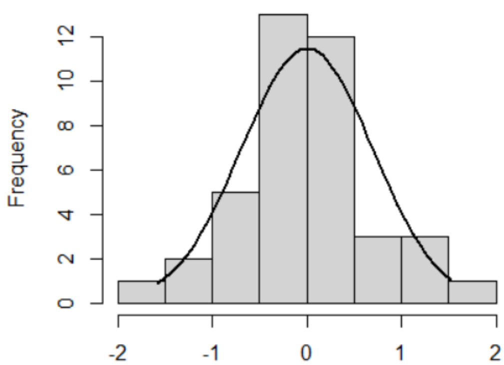


Figure 4: GDP residuals

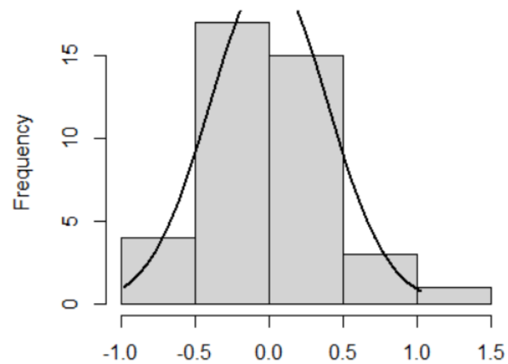


Figure 5: Unemployment residuals

Table 13: Skewness, Kurtosis, and normality tests' p-values

	GDP	Unemployment
Skewness	0.100	0.067
Kurtosis	3.292	3.257
Shapiro	0.428	0.999
Jarque-Bera	0.901	0.932
D'Agostino	0.770	0.843

The next assumption that we are going to test is whether $E(\epsilon|X) = 0$. To that end, I will run a LOESS regression, which is a non-parametric method. The advantage of this is that it does not assume any functional form of the relation of the residuals and the Xs.

Both in GDP and unemployment (figures 6 and 7) we can appreciate that the nonparametric regression looks straight along the zero line and that its confidence intervals always contain zero inside them. Therefore, they fail to reject that $E(\epsilon|X) = 0$.

Figure 6: GDP Residuals plot

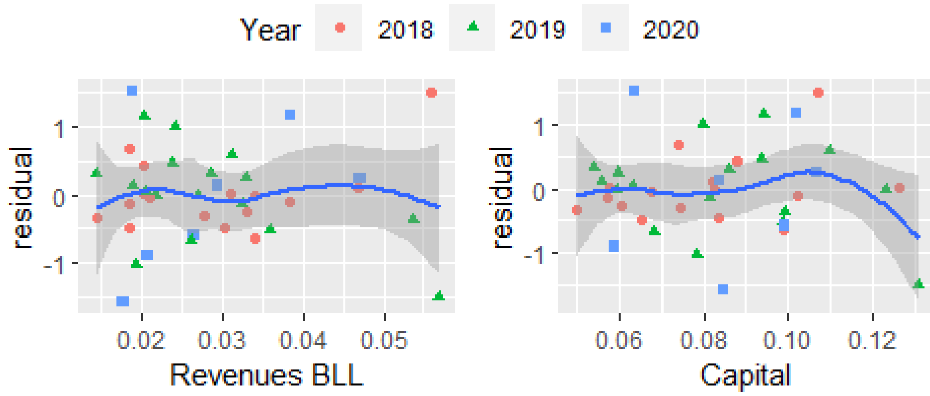
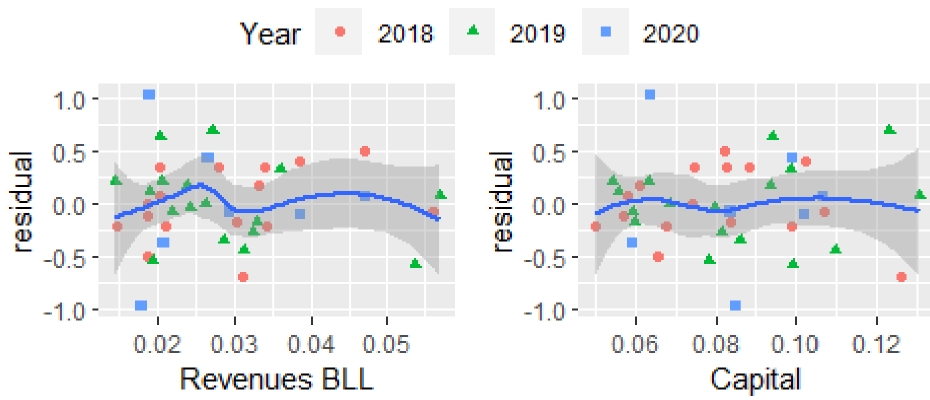


Figure 7: Unemployment residuals plot



Finally, I will conduct a robustness analysis. To that end, I will compute the Cook's distance of each observation, and repeat the regression without the points with the highest value. The Cook's distance is useful to detect influential outliers, since it is based both on how far away an observation is from the data in the independent variables (leverage) and how much it influences the estimated coefficient (residual).

As we can see in figures 8, 9, 10 and 11, all values are below 0.5, which is considered to be a good threshold. In addition, when we compute the regression again but without the potential outliers in table 14, we can appreciate not only that we still find capital management, but also that the revenues effect has disappeared.

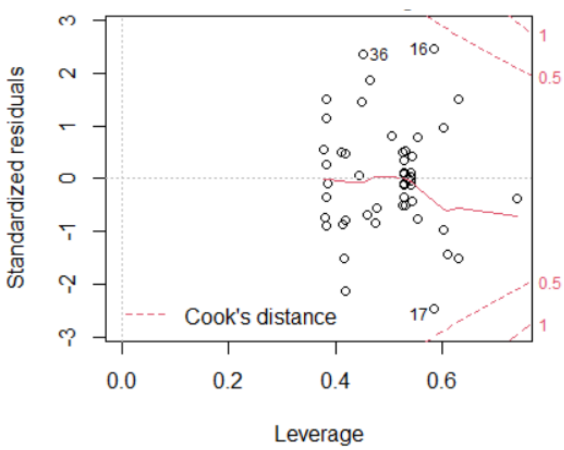


Figure 8: Residuals over leverage for GDP

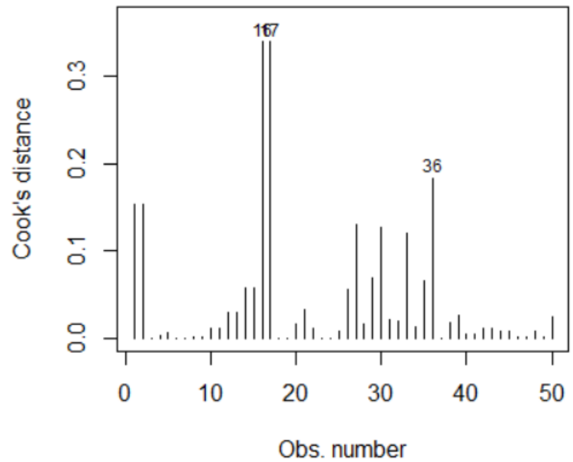


Figure 9: Cook's Distance for GDP

Table 14: Excluding potential outliers

	Dependent variable:					
	Optimism in GDP			Optimism in unemployment		
	(1)	(2)	(3)	(4)	(5)	(6)
Revenues_BLL	−4.513	−5.097	50.912	10.408	8.017	11.723
	(18.249)	(18.323)	(60.870)	(17.720)	(19.100)	(29.457)
Capital	7.413	8.064	24.659	7.829	11.101	27.702**
	(7.065)	(7.587)	(16.753)	(11.884)	(12.418)	(12.268)
Constant	−1.808***			−0.874		
	(0.685)			(0.732)		
Observations	47	47	47	47	47	47
Banks	21	21	21	21	21	21
R^2	0.020	0.023	0.241	0.071	0.110	0.167
Adjusted R^2	−0.024	−0.070	−0.518	0.029	0.025	−0.741
Time FE	No	Yes	Yes	No	Yes	Yes
Bank FE	No	No	Yes	No	No	Yes

Note: *p<0.1; **p<0.05; ***p<0.01
Heteroskedasticity consistent errors clustered at the bank level in all regressions

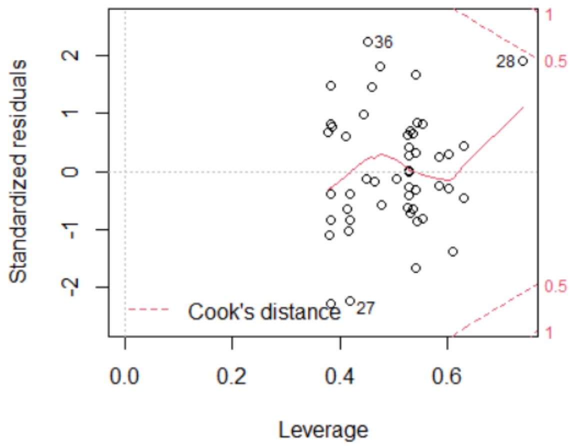


Figure 10: Residuals over leverage for unemployment

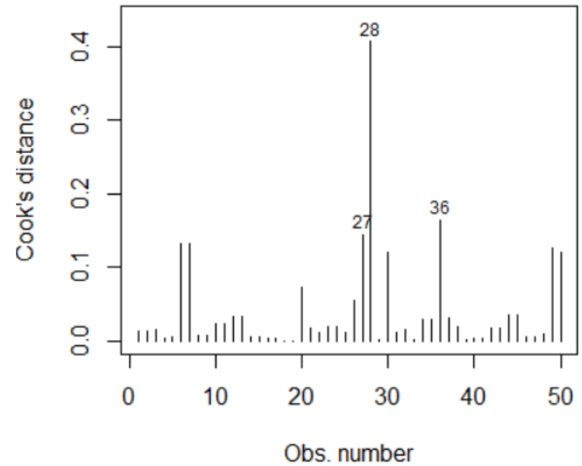


Figure 11: Cook's Distance for unemployment

7 Conclusions

There is a large body of literature about the use of Loan Loss Provisions (LLP) for the purpose of earnings and capital management. However, the results are rather inconsistent, mainly due to the different periods, countries and model specifications that have been used. In this thesis, taking advantage of the IFRS 9 standards that entered into application in 2018, I have been able to circumvent the usual endogeneity critique by using macroeconomic forecasting optimism as a proxy for discretionary LLP that should be exogenous to everything else. Not only banks should not manipulate LLP, but also IFRS 9 explicitly states that banks should use unbiased macroeconomic forecasts and disclose them.

Moreover, since there is no database with the data about banks' macroeconomic forecasts, I have directly collected this data from the banks' annual reports. There we can see that, for some reason, banks' forecasts about unemployment are in line with the IMF, but the GDP forecasts are generally more pessimistic.

In addition, only one third of the banks discloses the forecasts. I find that, as expected, bigger banks are more likely to disclose them. Nevertheless, I find that, for some reason, banks with a higher revenues ratio are less likely to disclose them. This may indicate that they undertake earnings management, although there is not enough evidence to affirm that.

Regarding the disclosed forecasted values, I compare them with the forecast of the IMF with the same specification to compute a measure of relative optimism, which should be exogenous in the case that the IMF and the banks use the same information. I find that, from the two opposed incentives that capital management gives – coming from Tier 1 capital and Total capital – the one from Total capital dominates the other. That is, the lower the capital, the lower the forecast used by banks, in order to have more LLP. This result is robust to different specifications and robustness analyses. Moreover, I find that, contrary to the earnings management incentive, there is a positive relation between Optimism and earnings, which may indicate that banks consider their revenues as an input to forecast the economy, and they weight it more than the IMF. However, this last result does not hold with the robustness analysis.

Finally, the robustness and residuals analyses were very important due to the small size of the sample. Even though the conclusions that I draw hold up to it, it would be important to do another study with a larger sample, to definitively check the robustness of the results. Moreover, I have seen that banks tend to manipulate their forecasts to manage capital through LLP. An interesting further research would be to analyse whether this management is higher or lower than during the previous LLP estimation method: the Incurred Loss model, where banks had a lower degree of discretion.

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