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2020

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This Version: 2020

To cite: Ozili, P.K. (2020). Bank loan loss provisioning during election year: cross-country evidence. International Journal of Managerial Finance, forthcoming.

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Abstract

I examine bank loan loss provisioning behaviour during election years - focusing on the effect of elections on banking sector loan loss provisioning. The findings reveal that the banking sectors in developed countries have higher loan loss provisions in election years. Income smoothing is present in election years which supports the income smoothing hypothesis. Also, banking sectors with high capital levels have higher loan loss provisions. Although there were no significant differences in bank loan loss provisioning during election years across the four bloc, the EU banking sectors and the banking sectors of BIS member-countries generally have higher loan loss provisions while the non-EU banking sectors and the banking sectors of the G7 member-countries generally have fewer loan loss provisions.

Keywords: loan loss provisions; income smoothing; election; banks; credit risk, nonperforming loans, institutional factors, corruption,

JEL Classification: G21, G28.

1. Introduction

Political candidates borrow money from banks to fund election campaigns, and there is the risk that loans for election campaigns may not be repaid or may be repaid later than the expiry date of the loan. If the borrower wins the election, banks often respond to this by writing off such loans or by restructuring the loans for delayed repayment of interest and principal. Whichever is done, the banks would have to increase loan loss provisions due to change in loan quality. After the candidate has won the election, the lending bank(s) can write off the loans with the expectation that the ruling party will, in return for the kindness shown by the bank, create a favourable business environment for the lending bank(s). If banks predict that the borrower(s) will lose the election after the loan had been disbursed to the borrower(s), banks would have already set-aside some loan loss provisions to mitigate this risk since banks are aware that it is difficult to compel politicians to pay their debt, which could lead to loan defaults, requiring banks to keep higher provisions. Furthermore, even when banks do not give loans to fund election campaign, banks will still increase general provisions in response to election uncertainties that may affect the loan portfolio of banks in the banking sector.

The above shows the potential effect of election events on bank financial reporting through loan loss loans and its overall effect on the banking sector. Yet, prior studies have not considered the effect of election events on bank provisioning. Prior studies show that loan loss provisions (LLPs) are important accruals in banks and are used to cover expected losses arising from the lending activity of banks (Curcio and Hasan, 2015; Leventis et al, 2011). LLPs have a signaling effect in the financial statements of banks in that they convey valuable information on the quality of banks' loan portfolio, and LLP can have significant effects on reported earnings and regulatory capital (Ozili and Outa, 2018). The current level of loan loss provisioning in banks is significantly influenced by both prudential regulation requirements, which emphasize higher provisioning, and accounting standard setting which emphasize greater transparency of banks' financial statements (Bushman and Williams, 2012). Given the focus on financial stability by bank regulators, bank regulators favour forward-looking provisioning, which allow banks to account for loss events that are expected but have not yet occurred and to build a buffer in anticipation of future losses and to enhance the stability of the bank capital over time (Bikker and Metzemakers, 2005; Laeven and Majnoni, 2003).

This paper investigates bank provisioning behavior during election years during the 1998 to 2016 period. I explicitly investigate the impact of the election-year on bank provisioning at the country level, while controlling for the level of political stability, corruption control and other factors. The ability to manipulate loan loss provisions derives mainly from the discretion that managers have in determining the appropriate level of provisions to set aside for their current exposures in their loan book. Ideally, the bank manager would consider a number of credit risk factors affecting the loan and will assign a credit risk weight to each risk factor. The risk weight would be higher if the risk is considered to be material. One risk that bank managers may consider alongside other credit risk factors is the effect of elections on banks' ability to recover loans from politically-connected obligors as well as the effect of elections on banks' ability to conduct business. I call this the 'election year' effect. The 'election year' becomes a country risk factor which banks will take into account if banks believe that a change in the current government following general elections may affect their ability to recover loans from politically-connected obligors. Such banks will keep additional loan loss provisions to mitigate the 'election year' effect which is also a type of country risk. Surprisingly, the extant literature has not examined the characteristics of bank financial reporting during election year despite the fact that banks are often the largest borrowers to fund election campaigns in most countries, and there is the risk that the loans issued to campaign borrowers may not be repaid in full, or at worst, will be written off. The findings reveal that the banking sectors in developed countries have higher loan loss provisions in election years, and there is evidence of income smoothing during election years. Also, banking sectors that have high capital levels also have higher loan loss provisions, among other findings.

This study makes three contributions to the literature. Firstly, it contributes to the literature that examine the role of loan loss provisions for effective risk management (e.g., Jin et al, 2018; Ozili and Outa, 2017; Cohen et al, 2014). By focusing on loan loss provisions, I provide insights to understand how the level of bank provisions may be driven by the need to set-aside additional provisions 'buffer' to mitigate other risks emanating from bank lending other than the usual obligor-related credit risk factors. Secondly, this study contributes to the literature that investigate the influence of external and institutional factors on bank financial reporting behaviour (e.g., Ozili, 2019a; Bikker and Metzemakers, 2005; Laeven and Majnoni, 2003; Fonseca and Gonzalez, 2008). By controlling for election year effect, political stability and level of corruption, I provide insights to understand how unique factors in a country can influence the behavior of loan loss provisions in banks. Thirdly, this study examines the behavior of loan loss provisioning in the banking sectors of developed economies where elections are more regular, transparent and free from structural barriers, which makes it a natural setting to test the effect of election-year on banks financial reporting, focusing on loan loss provision in this study.

The remainder of the paper is organized as follows. Section 2 provides an overview of the relevant literature. Section 3 presents the data and methodology. Section 4 discuss the empirical results. Section 5 concludes.

2. Literature review

Loan loss provisions are classified into its discretionary and non-discretionary components. Non-discretionary loan loss provisions are credit-related factors that drive the level of loan loss provisions while discretionary loan loss provisions are other non-credit considerations and opportunistic considerations that drive the level of provisions. Although the main function of LLPs is to cover expected credit losses, they can be manipulated to pursue other managerial objectives such as income smoothing (Ahmed et al., 1999; Balla and Rose, 2015), capital management (Curcio and Hasan, 2015; Leventis et al., 2011; Ozili, 2015) and signaling of bank's financial strength (Kanagaretnam et al, 2005; Anandarajan et al, 2007), among others.

Prior studies have examined bank loan loss provisioning under several contexts and under certain events but none of these studies have considered the effect of the election event on bank provisioning. For instance, Leventis et al (2011) examine the discretionary determinants of loan loss provisions for listed European banks, and find that earnings management (using loan loss provision) was prevalent among 91 listed EU banks but this behavior was significantly reduced after the implementation of the International Financial Reporting Standard (IFRS). Kilic et al (2012) examine the impact of SFAS 133 on the informativeness of loan loss provisions for banks in the US. They find that banks used loan loss provisions for income smoothing purposes which reduced the informativeness of loan loss provision estimates. El Sood (2012) considered the effect of financial crises on the ability of banks to use loan loss provisions to smooth income.

Using a sample of 878 US bank holding companies from 2001 to 2009, the findings reveal that US banks use provisions to smooth income when they are meet the minimum regulatory capital ratio, when they are in non-recessionary periods, and when they are more profitable. Olszak et al (2017) examine the cyclicality of loan loss provisions in the EU, and find that loan loss provisions are procyclical in large, publicly-traded and commercial banks, however, strong capital standards and better investor protection weakened the procyclicality of LLP.

Marton and Runesson (2017) examine the predictive ability of loan loss provisions with respect to actual losses under IFRS and local GAAP standards. They find that loan loss provisions in IFRS bank-years predict future credit losses to a lesser extent than in local GAAP bank-years. Local GAAP also performed relatively better than IFRS in large, and in profitable, banks; however, the benefits of local GAAP are largely limited to high-enforcement settings. Cummings and Durrani (2016) investigate the effect of the Basel Accord capital requirements on banks provisioning and show that bank managers use their discretion in setting the level of loan loss provisions to dampen the impact of fluctuations in credit market conditions on their lending activities. Ozili (2018) investigates the non-discretionary determinants of bank loan loss provisions in Africa and show that bank loan loss provision is a positive function of non-performing loans up to a threshold beyond which bank provisions will no longer increase as non-performing loans increases. Ozili (2019b) also examine the relationship between loan loss provisions and bank intangibles among African banks and show that higher discretionary loan loss provisions are associated with few intangible assets in banks, but the inverse association is weakened in environments with strong investor protection.

Bratten et al (2017) examine whether banks' use of the loan loss provision to manage earnings is influenced by the extent to which banks hold assets subject to fair value reporting and the use of an industry specialist auditor. They find that banks with a greater proportion of assets subject to fair value reporting (i.e., higher fair value exposure) use less LLP-based earnings management techniques but more transaction-based earnings management (i.e., earnings management achieved by timing the realization of gains or losses. They also find that banks engaging industry specialist auditors use less LLP-based earnings management. Murcia et al (2016) examine the determinants of loan loss provisions and delinquency ratios for 554 banks from emerging market economies (EMEs), and find that bank loan loss provisioning in emerging market economies respond mostly to aggregate (macro-) variables, and very little to idiosyncratic (bank-specific) factors. Curcio and Hasan (2015) find that non-Euro Area credit institutions use loan loss provisions for income smoothing purposes more than for capital management and signaling purposes.

Country-specific studies also report some determinants of the level of loan loss provisions. In the United States, Morris et al (2016) examine the economic determinants and value relevance of US banks' loan loss provisions during the global financial crisis. They find that discretionary provisions are used for smoothing and signaling when the two incentives reinforce each other, but smoothing occurs more frequently. Kanagaretnam et al (2005) show that US banks use loan loss provisions to signal information about banks future prospects but the propensity to use provisions for signaling purposes is greater among smaller banks. In Italy, Caporale et al (2018) examine the determinants of loan loss provisions among 400 Italian banks during 2001 to 2015. They find that loan loss provisions in Italian banks were significantly influenced by the non-discretionary components of loan loss provisions. However, the procyclicality of loan loss provisions was less pronounced for local banks because their loans were well collateralized and their behaviour was more strongly affected by supervisory activity. In China, Wang et al (2019) examine whether bank loan loss provisions affect credit fluctuation in China's banking system, and find that non-discretionary loan loss provisions have a significant impact on credit fluctuation whereas discretionary loan loss provisions have no significant impact on credit fluctuation for Chinese banks. In South Africa, Ozili and Outa (2018) show that South African banks do not use LLPs to smooth income when they are: under-capitalized, have large non-performing loans and have a moderate ownership concentration; however, using LLP to smooth income is pronounced when South African banks are more profitable during economic boom years, when they are well-capitalized and is pronounced among banks that adopt IFRS and have a Big 4 auditor. In Poland, Borsuk (2019) conducted a set of stress test scenarios to determine how different economic scenarios would affect loan loss provisions among other financial ratios. Borsuk find that economic growth, the labour market and market interest rates have a significant influence on the loan loss provision ratio of banks in Poland. In Uruguay, Gambetta et al (2016) focused on the regulatory reporting of loan loss provisions to bank supervisors. They suggest that data analytics such as enterprise resource planning (ERP) system and the eXtensible Business Reporting Language (XBRL) have great benefits to improve bank's reporting of loan loss provisions by banks in Uruguay. Generally, the evidence for the determinants of loan loss provisions are mixed in the literature, yet the extant literature has not examined the effect of elections on the financial reporting and performance of banks both at the bank-level and at the country-level.

3. Data and Methodology

3.1 Data

Data was obtained for 35 developed countries. The countries were chosen based on the United Nation's list of developed countries[1]. Developed countries were used in the study because developed countries have more regular elections compared to developing countries and transition economies. Also, developed economies do not experience coup (i.e., overthrow of government) or dictatorship that prevent elections from taking place, meanwhile all these are prevalent in transition economies and in developing economies.

Financial statement data for the countries were obtained from the World bank database. Some financial data were available while other financial data were not available but were computed as a derivative of two or more available data. The sample period covers the 1998 to 2016 period and is sufficient to cover at least 5 election cycles. Data for real gross domestic product growth rate was collected from the World Economic Forum archived in the World Bank database while institutional data was collected from the World Governance Indicators database of the World bank. Election data was obtained from public sources such as government websites, Wikipedia and other public sources. See Appendix 1 for source of data and variable description.

3.2. Methodology

The baseline model to estimate the behavior of loan loss provisions during election years is given below. The model below is a modified version of the models used in prior literature (see Curcio and Hasan, 2015; Jin et al, 2018; Ozili, 2019; Wheeler, 2019).

[1] The UN List of developed countries can be found here: https://www.un.org/development/desa/dpad/wp-content/uploads/sites/45/WESP2019_BOOK-ANNEX-en.pdf

$$LLPi,t = c + ELECTi,t + NPLi,t + CRISISi,t + \Delta GDPi,t + PSi,t + CCi,t + LAWi,t + LGi,t + e \dots\dots\dots\dots 1$$

Where,

LLP = ratio of loan loss provisions to gross loans in the banking sector of each country

NPL = ratio of nonperforming loans to gross loans in the banking sector of each country

ELECT = a binary variable that equal one in election years and zero in non-election years

CRISIS = a binary variable that equal one in a banking or financial crisis year and zero otherwise

ΔGDP = real domestic product growth rate in each country

CC = control of corruption index, the higher the better

PS = political stability / absence of terrorism index; the higher the better

LAW = rule of law index, reflecting the quality of legal system and enforcement; the higher the better.

LG = ratio of credit provided to the private sector by banks as a share of GDP in each country

t = year

i = country

The model above expressed loan loss provisions ratio as a function of non-discretionary[2] LLP determinants (NPL & ΔGDP) and other external determinants (political factors and institutional factors).

The LLP ratio is the dependent variable, and was derived by multiplying the NPL ratio data with the loan loss coverage ratio data obtained from the World bank, using the formula below:

$$LLP / GL = (NPL / GL) * (LLP / NPL)$$

Where NPL ratio = nonperforming loans divided by gross loan; the loan loss coverage ratio = actual amount of loan loss provisions divided by actual amount of nonperforming loans.

For the explanatory variables, the ELECT variable is the main variable of interest because it captures the election years in developed country in the sample. A positive sign for the ELECT coefficient is expected if the banking sector substantially increase its level of provisions in response to election uncertainties that may affect the loan portfolio of banks in the banking sector. For instance, banks that have high exposure to political debtors may experience difficulties in compelling politicians to pay their debt, which could lead to loan defaults, requiring banks to keep higher provisions.

For the control variables, prior studies control for the non-discretionary determinants of loan loss provisions (e.g. Ahmed et al, 1999; Ozili and Outa, 2017). The nonperforming loan (NPL) variable is introduced into the model to control for bank provisioning in response to increasing bad loans. Prior literature shows that

[2] Other non-discretionary LLP determinants that were used in prior literature include: loan to asset ratio, loan charge-offs, loan growth etc, and these variables are only observable at bank-level but not at country-level. This is reason why only the NPL and ΔGDP variables have been used in this study as non-discretionary determinants of LLP in the LLP modeling in equation 1.

banking sectors that have high nonperforming loans will keep higher provisions (see Laeven and Majnoni, 2003; Bikker and Metzemakers, 2005; Ozili and Outa, 2017); thus, a positive sign is predicted for the NPL coefficient. The real gross domestic product growth rate (ΔGDP) variable is introduced into the model to control for bank provisioning along the economic cycle. Generally, the banking sectors tend to have fewer provisions during good economic times and higher provisions during bad economic times. This expectation is consistent with prior studies that show that banks keep fewer provisions in economic boom periods because they expect fewer loan defaults in good times, and keep more provisions in recessionary periods because the probability of default is higher during bad times (see Laeven and Majnoni, 2003, Ozili, 2018); implying a negative relationship between ΔGDP and LLP. The total loan to GDP (LG) ratio is introduced into the model to reflect the extent to which the economy is driven by private credit. The LG ratio measures the amount of credit provided to the private sector by banks as a share of GDP. Banks in highly credit-driven economies would normally keep higher general provisions to mitigate contemporaneous credit risk in their loan portfolio, thus, a positive relationship between LLP and LG is expected. The LG ratio is derived mathematically by multiplying the credit to deposit ratio data with the bank deposit to GDP data in the World bank database, using the formula below.

$$LOAN\ /\ GDP\ =\ (LOAN\ /\ BANK\ DEPOSIT)\ *\ (BANK\ DEPOSIT\ /\ GDP)$$

Next, it is important to control for the impact of the prevailing political environment on elections which can affect the banking sector. To do this, I introduce three institutional factors (the corruption control (CC), rule of law (LAW) and the political stability (PS) indicators) that play a significant role during elections. Corruption levels and political instability have been considered to be detrimental to general elections (Dupas and Robinson, 2012; Callen and Long, 2015), and there is also some evidence that strong legal systems can improve election outcomes (Gibson et al, 2003). The PS variable is introduced into the model. Higher values of PS indicate greater political stability, and a negative relationship between LLP and PS is expected because, Ghosh (2016) show that banks in politically unstable environments tend to perform poorly - they have low profitability and higher nonperforming loans; in such environments, banks would keep higher provisions to cover expected losses that may arise from political instability. For the CC variable, a negative relationship between LLP and CC is expected because banks in highly corrupt environments will experience higher nonperforming loans (Goel and Hasan, 2011), requiring banks to keep higher loan loss provisions. Higher values of CC indicate greater control of corruption. For the LAW variable, a negative relationship between LLP and LAW is expected because banks in strong legal environments are able to use the power of the courts to compel debtors to repay their debt which reduces the level of nonperforming loans (Cristini et al, 2001), thereby leading to fewer provisions. Higher values of LAW indicate greater legal quality and enforcement. Table 1 presents a summary of the expected signs of the variables. Finally, the models are estimated using fixed effect regression model.

(Insert Table 1)

4. Empirical Results

4.1. Descriptive Statistics and Correlation

4.1.1. Descriptive statistics

Table 2 report the summary of the descriptive statistics of the variables. Loan loss provisions averages 2.87% of gross loan. LLPs are higher in the banking sectors of Greece, Cyprus and Romania, and are much lower for Canada and Australia. Non-performing loans (NPL) averages 5.18%, and is a double-digit higher for Cyprus, Croatia and Italy. The high NPLs indicate that the banking sectors of these countries have low asset quality; comparatively, NPLs are lower in the banking sectors of Canada, Luxembourg and Australia. ΔGDP, on average, is about 2.42% and is much lower for Greece and Italy and is higher for Lithuania and Latvia. Overall, the result from the descriptive statistics suggest that there is wide variation across banking sectors in developed countries.

(Insert Table 2)

4.1.2. Correlation

Table 4 report the Pearson correlation coefficients and the associated p-values. LLPs are positive and weakly correlated with the ELECT variable (0.057), however, the correlation between LLP and ELECT is not significant. LLPs are negative and significantly correlated with ΔGDP (-0.108*), indicating that provisioning in the banking sector is procyclical with fluctuations in the business cycle. The LAW and CRISIS coefficients are positive and significantly correlated with LLPs. This indicate that higher loan loss provisions are higher in countries that have strong legal enforcement and in countries that experience financial crises. The PS and CC coefficients are negatively correlated with LLPs, and indicate that banking sectors in political stable and less corrupt environments have fewer provisions. Also, NPL is positively correlated with LLPs and indicate that loan loss provisions are higher in banking sectors that experience higher nonperforming loans. LG is also negatively correlated with LLPs and indicate that loan loss provisions are higher in credit-driven economies. Table 3 report the Pearson correlation coefficients for the country variables.

(Insert Table 3)

4.2. Regression Results

4.2.1. Bank Provisioning behavior during election year

The estimation results are reported in Table 4. The ELECT coefficient is positively significant at the 5% level in model (1), indicating that the election year had a positive and significant impact on the loan loss provisioning of the banking sector in developed countries. This result implies that the banking sectors of developing countries have higher loan loss provisions during election years. The result remains significant when the GMM and OLS estimators are used to estimate the model.

For the control variables, the NPL coefficient is positively significant as expected, and is consistent with Laeven and Majnoni (2003) and Bikker and Metzemakers (2005). This implies that the banking sector of developed economies keep more provisions when banks expect higher non-performing loans. The ΔGDP, PS and CRISIS coefficients are not significant. The LAW coefficient is negatively significant, and is consistent with the apriori expectation that banks in strong legal environments are able to use the power of the courts to compel debtors to repay their debt which reduces the risk of loan defaults, thereby leading to fewer provisions. The CC coefficient is also negatively significant, indicating that the banking sectors in less corrupt countries have fewer loan loss provisions. The LG coefficient is positively significant at the 10% level, indicating that the banking sector of highly credit-driven economies have higher provisions. This result is consistent with the expectation that credit-driven economies tend to keep higher provisions to mitigate contemporaneous credit risk. Finally, some control variables yield different signs when alternative estimations are used to estimate the model as shown in model (2) and (3).

(Insert Table 4)

4.2.2. Classification by Regional and Political Bloc

Most regional and political blocs require its members to adopt a uniform set of regulatory and supervisory mechanisms or standards for banking regulation and supervision in member countries. Such uniform supervisory mechanisms for member countries may influence the extent of lending and provisioning for bad loans in the banking sectors of member countries. Here, I consider the case of member-countries in the European Union, the G7 also referred to as 'most developed economies (MDE), and the member countries of the Bank of International Settlement[3] (BIS). I estimate the differences in banking sector provisioning during election years for EU, non-EU, BIS and G7 countries. Binary variables were used to divide the sample into European Union (EU), non-European Union (non-EU), BIS member-countries and the G7 countries (MDE). The 'EU' binary variable is assigned a value of one if the developed country is a member of the European union and zero otherwise, the 'non-EU' binary variable is assigned a value of one if the developed country is not a member of the European union and zero otherwise, and the 'MDE' binary variable is assigned a value of one if the developed country is a member of the G7 countries.

$$LLPi,t \ = \ c + ELECTi,t + NPLi,t + CRISISi,t + \ \Delta GDPi,t + PSi,t + CCi,t + LAWi,t + \ LGi,t + ELECTi,t * EUi + ELECTi,t * Non - EUi + ELECTi,t * MBEi + e \dots\dots 2$$

The estimation results are reported in Table 5. The EU and BIS coefficient is positively significant at the 5% level in column 1, which suggest that the EU banking sectors and the banking sectors of BIS member-countries have higher loan loss provisions. On the other hand, the 'non-EU' and 'MDE' coefficients are negatively significant, which suggest that non-EU banking sectors and the banking sectors of the G7 member-countries have fewer loan loss provisions. Furthermore, the ELECT*EU, ELECT*Non-EU, ELECT*MDE, and ELECT*BIS coefficients are not significant and suggests that there were no significant differences in bank provisioning during election years across the four bloc.

(Insert Table 5)

[3] The mission of the BIS is to promote monetary and financial stability in the financial system of member countries. Sufficient provisioning can act as a cushion to absorb some unexpected losses in abnormal periods, thereby contributing to financial stability.

4.3. Further analyses

4.3.1. Income smoothing during election years

I test the income smoothing hypothesis to determine whether income smoothing using loan loss provisions is present in the banking sector of developed countries. The ideal income smoothing variable used in prior literature is a bank-level variable measured as 'earnings before profit and tax divided by total assets' however this variable is unobservable at the country level and therefore cannot be used in the country-level analyses in this study. A proxy variable was constructed using the available earnings variables at the country-level. The first earnings variable introduced into the model is the before-tax return on assets (ROA) variable. The second earnings variable is the net interest margin (NIM) variable. The third earnings variable is the provisions-adjusted ROA variable 'EBTP' computed using the formula: ROA*(1+LLP/100). The purpose of this adjustment is to create a replica of the "earnings before tax and provisions' variable traditionally used in prior literature by adding back provisions into the earnings variable. The fourth earnings variable is the provisions-adjusted NIM variable 'EBTP2' computed using the formula: NIM*(1+LLP/100). The purpose of this adjustment is also to create a corresponding replica of the "earnings before tax and provisions' variable traditionally used in prior literature by adding back provisions into the earnings variable. Also, a lagged election year variable (ELECTt-1) is introduced into the model to account for any pro-active provisioning in banks ahead of the election year. Banks can increase provisions early in the years before the election so that they do not have to keep too much provisions in the actual election year. Finally, the earnings variables are interacted with the 'ELECT' and 'ELECTt-1' variables as shown in equation 3 to determine whether determine whether income smoothing using loan loss provisions is present in the banking sector of developed countries during and before the election year. The result is reported in table 6.

$$
\begin{aligned}
LLPi,t \; = \; & c + ELECTi,t + NPLi,t + CRISISi,t + \; GDPi,t + PSi,t + CCi,t + LAWi,t + \; LGi,t \\
& + \; ELECTi,t-1 + \; ELECTi,t-1 * EBTP + ELECTi,t-1 * EBTP2 + ELECTi,t-1 \\
& * ROA + ELECTi,t-1 * NIMi,t + ELECTi,t * EBTPi,t + ELECTi,t * EBTP2i,t \\
& + \; ELECTi,t * ROAi,t + ELECTi,t * NIMi,t + e \ldots\ldots\ldots..3
\end{aligned}
$$

The ELECT*EBTP2, ELECT*NIM ELECTt-1*EBTP2 and ELECTt-1*NIM coefficients are positively significant at the 5% level, indicating that income smoothing is present in the banking sectors of developed countries. The finding support prior literature that show that banks have some incentive to manipulate loan loss provisions estimate for income smoothing purposes (Bushman and Williams, 2012; Ozili and Thankom, 2018)

(Insert Table 6 here)

4.3.2. Capital Management during election years

We also test the capital management hypothesis to determine whether capital management using loan loss provisions is present in the banking sector of developed countries. The CAR and CAP variables were introduced into the model. The CAR variable is the ratio of bank regulatory capital to risk-weighted assets while the CAP variable is the ratio of bank capital to total assets (%). Subsequently, the CAR and CAP earnings variables were interacted separately with the 'ELECT' and 'ELECTt-1' variables to determine whether determine whether income capital management using loan loss provisions is present in the banking sector of advanced countries during and before the election.

$$LLPi,t = c + ELECTi,t + NPLi,t + CRISISi,t + GDPi,t + PSi,t + CCi,t + LAWi,t + LGi,t + ELECTi,t-1 + ELECTi,t-1 * CARi,t + ELECTi,t-1 * CAPi,t + ELECTi,t * CARi,t + ELECTi,t * CAPi,t + CARi,t + CAPi,t + e$$

The result is reported in table 6. The ELECT*CAR and ELECT*CAR coefficients are positively significant at the 5% level, indicating that banking sectors with high capital levels have higher provisions. This implies that banking sectors in developed economies have sufficient provisions even when they are well-capitalized. However, this finding does not support the capital management hypothesis in the literature.

(Insert Table 6)

5. Conclusion

I examined bank provisioning behaviour during election years - focusing on the effect of elections on banking sector provisioning. I examined the banking sectors of 35 developed countries from 1998 to 2016. The findings reveal that the banking sectors in developed countries have higher provisions in election years. Also, income smoothing is present in election years which supports the income smoothing hypothesis. Also, banking sectors with high capital levels have higher provisions. Although there were no significant differences in bank provisioning during election years across the four bloc, the EU banking sectors and the banking sectors of BIS member-countries generally have higher loan loss provisions while the non-EU banking sectors and the banking sectors of the G7 member-countries generally have fewer loan loss provisions.

The main message of this paper is that the ‘election year’ is a significant country risk factor to banks because the uncertainty about election outcomes may affect the loan portfolio of banks especially when election campaigns are funded by loans from the banking sector, requiring banks to keep higher provisions to mitigate expected credit losses.

One implication of the findings is that political events such as elections, can have significant effect on the provisioning decisions of banks. More so, political events may affect other accounting numbers in banks not only loan loss provisions. Secondly, bank supervisors should consider the ‘election-year effect’ in their assessment of the appropriate level of regulatory provisions that banks should keep. One idea is to require banks to increase its stock of ‘general provisions’ in election years to act as a cushion to mitigate expected and unexpected losses arising from election and post-election events. Thirdly, strong legal and political institutions can help to reduce the negative effects of elections on bank stability and performance, therefore, policy makers should develop policies that strengthen existing institutions with the appropriate enforcement powers.

Future research should investigate other cross-country events that can affect the stability of the banking sector across countries. Future research can also investigate the effect of elections on bank provisioning in developing and transition countries. Such future studies should take into account the fact that most developing and transition countries either have irregular elections or experience political and military events that may prevent elections from taking place.

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Appendix

Appendix 1: Variable Description		
Indicator Name	Short definition	Source
LLC	Provisions to nonperforming loans (%)	Financial Soundness Indicators Database (fsi.imf.org), International Monetary Fund (IMF)
ΔGDP	Gross domestic product growth rate	World Bank national accounts data, and OECD National Accounts data files.
LG	Credit to private sector by banks as a share of GDP.	Bankscope, Bureau van Dijk (BvD)
CAP	Ratio of capital to total asset	
CAR	Bank regulatory capital to risk-weighted assets (%)	Financial Soundness Indicators Database (fsi.imf.org), International Monetary Fund (IMF)
NPL	Bank nonperforming loans to gross loans (%)	Financial Soundness Indicators Database (fsi.imf.org), International Monetary Fund (IMF)
PS	Political stability and absence of terrorism	World Governance Indicator in the world bank database
CC	Control of corruption	World Governance Indicator in the world bank database
LAW	Rule of law / quality of legal system	World Governance Indicator in the World bank database
ELECT	Election year variable	Constructed by author
CRISIS	The financial crisis indicator	Global financial development indicator in the World bank database
NIM	Net interest margin	Global financial development indicator in the World bank database
ROA	Return on assets, before tax	Global financial development indicator in the World bank database
EBTP 1	Income smoothing variable (earnings before tax and provisions)	Constructed by author
EBTP 2	Another income smoothing variable (earnings before tax and provisions)	Constructed by author

Table 1

Table 1: Information about the variables		
Variable	Expected/Predicted Sign	Description
LLP	Dependent Variable	Loan loss provisions divided by total asset ratio
ELECT	(+)	Election year
NPL	(+)	Non-performing loans to gross loans ratio
LG	(+)	Private credit supply to the economy
LAW	(-)	Rule of law / quality of legal system; Rule of law index
PS	(-)	Political stability and absence of terrorism index
CC	(-)	Corruption control index
ΔGDP	(-)	change in real gross domestic product

Table 2

Table 2: Country Descriptive Statistics (Mean values)										
S/N	Countries	LLP	NPL	ELECT	ΔGDP	PS	LAW	CRISIS	CC	LG
1	Canada	0.32	0.88	0.31	2.35	1.07	11.35	0	1.97	105.55
2	United States	1.06	1.95	0.26	2.28	0.46	10.94	0.36	1.48	51.19
3	Japan	1.33	3.38	0.36	0.71	1.04	10.58	0.29	1.38	116.22
4	France	2.59	4.21	0.15	1.56	0.48	10.53	0.29	1.38	86.88
5	Germany	1.73	3.66	0.26	1.42	0.90	10.47	0.28	1.83	96.48
6	Italy	4.99	10.24	0.21	0.44	0.54	10.94	0.28	0.28	76.84
7	United Kingdom	1.24	2.33	0.21	2.032	0.47	10.35	0.35	1.83	-
8	Norway	0.65	1.212	0.21	1.76	1.29	10.29	0	2.12	88.56
9	Iceland	3.19	4.66	0.31	3.41	1.36	8.64	0.28	2.08	136.36
10	Switzerland	0.60	1.52	0.26	1.94	1.33	9.82	0.28	2.09	153.37
11	Sweden	0.52	1.11	0.26	2.54	1.21	10.35	0.28	2.22	110.81
12	Spain	2.64	3.47	0.31	2.05	0.02	10.52	0.28	1.09	127.55
13	Portugal	3.66	5.51	0.21	0.92	0.98	10.23	0.28	1.07	128.28
14	Netherland	0.73	2.52	0.31	1.77	1.09	10.17	0.28	2.069	114.77
15	Luxembourg	0.21	0.45	0.21	3.51	1.42	7.65	0.28	1.98	83.93
16	Ireland	3.70	7.88	0.10	5.37	1.15	9.82	0.28	1.57	104.95
17	Greece	7.64	14.83	0.26	0.51	0.24	10.52	0.28	0.19	79.34
18	Finland	0.37	0.54	0.15	1.90	1.45	10.05	0	2.31	72.87
19	Denmark	1.27	2.36	0.26	1.35	1.11	10.05	0.28	2.36	152.57
20	Belgium	1.42	2.86	0.26	1.69	0.84	10.17	0.28	1.48	61.51
21	Austria	1.90	2.65	0.21	1.76	1.16	10.17	0.28	1.74	90.91
22	Australia	0.34	0.97	0.36	3.19	0.98	10.05	0	1.93	105.79
23	New Zealand	0.39	1.15	0.32	2.81	1.33	10.24	0	2.30	122.00
24	Slovenia	4.13	7.22	0.15	2.37	1.04	13.05	0.28	0.91	54.62
25	Romania	11.43	14.76	0.21	3.32	0.18	14.52	-	-0.25	22.80
26	Poland	5.09	8.89	0.21	3.75	0.71	14.41	0	0.51	37.27
27	Malta	1.91	7.32	0.21	3.72	1.26	6.88	0	0.86	101.74
28	Lithuania	3.72	9.21	0.32	4.07	0.75	12.94	0	0.35	34.13
29	Latvia	3.35	5.27	0.32	3.96	0.53	12.52	0.28	0.26	49.82
30	Hungary	3.69	6.98	0.21	2.34	0.84	13.94	0.28	0.48	43.94
31	Estonia	0.84	1.66	0.21	3.76	0.70	13.35	0	1.02	61.34
32	Cyprus	9.14	24.69	0.21	2.48	0.49	8.47	0	1.05	174.58
33	Czech Republic	4.47	8.23	0.21	2.55	0.94	13.71	0.21	0.38	42.94
34	Croatia	5.85	10.05	0.32	1.74	0.55	13.47	0.14	0.08	53.48
35	Bulgaria	6.05	9.74	0.22	3.19	0.27	14.12	0	-0.15	41.68
	Total	**2.87**	**5.18**	**0.25**	**2.42**	**0.86**	**11.01**	**0.19**	**1.27**	**87.14**

Table 3

Table 3: Correlation Matrix

Variable	LLP	NPL	ELECT	ΔGDP	PS	LAW	CRISIS	CC	LG
LLP	1.000								
NPL	0.921***	1.000							
	(41.31)								
ELECT	0.057	0.021	1.000						
	(1.01)	(0.36)							
ΔGDP	-0.108*	-0.184***	0.011	1.000					
	(-1.91)	(-3.28)	(0.19)						
PS	-0.375***	-0.316***	-0.044	0.052	1.000				
	(-7.09)	(-5.83)	(-0.77)	(0.91)					
LAW	0.218***	0.249***	-0.046	-0.037	-0.329***	1.000			
	(3.92)	(4.52)	(-0.81)	(-0.61)	(-6.11)				
CRISIS	0.169***	0.222***	0.001	-0.439***	-0.135**	0.143**	1.000		
	(3.01)	(3.98)	(0.02)	(-8.56)	(-2.38)	(2.54)			
CC	-0.516***	-0.508***	0.034	-0.128**	0.587***	-0.561***	0.060	1.000	
	(-10.56)	(-10.34)	(0.59)	(-2.27)	(12.71)	(-11.87)	(1.06)		
LG	-0.209***	-0.179***	0.039	-0.385***	0.203***	-0.307***	0.298***	0.554***	1.000
	(-3.76)	(-3.19)	(0.69)	(-7.31)	(3.63)	(-5.66)	(5.48)	(11.67)	

***, **, * denotes 1%, 5% and 10% significance level.

Table 4

Table 4: Impact of elections on provisioning in the banking sector			
	(1)	(2)	(3)
	Fixed effect)	GMM	OLS
Variables	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)
c	3.164*** (3.67)	-	-
LLPt-1		0.109*** (4.96)	
ELECT	**0.195** (2.15)**	**0.093*** (3.27)**	**0.194* (1.72)**
NPL	0.448*** (30.30)	0.413*** (21.16)	0.471*** (36.91)
CRISIS	0.142 (0.86)	-0.596 (-1.51)	-0.113 (-0.84)
ΔGDP	0.018 (0.87)	-0.0002 (-0.01)	0.049*** (3.00)
PS	-1.146 (-0.56)	-1.111*** (-3.79)	-0.464*** (-3.11)
CC	-0.187*** (-2.83)	1.0728*** (3.45)	0.122 (1.16)
LAW	-0.187*** (-2.83)	0.170*** (4.00)	0.028** (2.24)
LG	0.005* (1.91)	0.007 (1.103)	0.001 (0.37)
R^2	92.83		99.78
Adjusted R^2	91.42		99.40
F-statistic	65.33		261.62
Prob (F-statistic)	0.000		0.00004
J-statistic		13.19	
Prob(J-statistics)		0.51	
No of Observation (adjusted)	309	240	309

Model (2) is estimated using GMM first difference regression (with ordinary coefficient covariance method and tick the box "do not transform period dummies" effects specification). Model (1) is estimated using fixed effect regression (with country and year fixed effects). Model (3) is estimated using ordinary OLS with no fixed effects. NPL = ratio of nonperforming loans to gross loans: the lower the better; ELECT = a binary variable that equal one in an election year and zero in non-election year. CRISIS = a binary variable that equal one in a financial or banking or economic crisis year and zero otherwise. ΔGDP = real domestic product growth rate; CC = control of corruption index: the higher the better; PS = political stability / absence of terrorism index: the higher the better; LAW = rule of law index; the higher the better. LG = ratio of credit provided to the private sector by banks as a share of GDP. LLP = is the one-year lag of the loan loss provisions variable. ***, **, * denotes 1%, 5% and 10% significance level.

Table 5

Table 5: Bank Provisioning during election years in EU, non-EU, BIS and G7 countries								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)
C	-0.849 (-1.59)	-0.562 (-1.09)	-0.365 (-0.69)	-0.883 (-1.68)	-0.862 (-1.61)	-0.556 (-1.07)	-0.338 (-0.64)	-0.921 (-1.70)
ELECT	0.219** (2.06)	0.219** (2.06)	0.211** (1.99)	0.195* (1.85)	0.268 (1.16)	0.204* (1.70)	0.177 (1.49)	0.389 (0.59)
NPL	0.458*** (32.09)	0.458*** (32.09)	0.459*** (32.26)	0.465*** (32.82)	0.458*** (32.02)	0.458*** (32.02)	0.459*** (32.23)	0.464*** (32.71)
CRISIS	0.313** (2.13)	0.313** (2.13)	0.372** (2.55)	0.187 (1.21)	0.313** (2.13)	0.313** (2.13)	0.375** (2.57)	0.189 (1.21)
ΔGDP	0.028 (1.39)	0.028 (1.39)	0.023 (1.10)	0.040* (1.93)	0.028 (1.39)	0.029 (1.39)	0.024 (1.13)	0.039* (1.89)
PS	-0.591*** (-4.02)	-0.591*** (-4.02)	-0.605*** (-4.09)	-0.465*** (-3.19)	-0.593*** (-4.02)	-0.594*** (-4.02)	-0.615*** (-4.12)	-0.465*** (-3.18)
CC	0.079 (0.68)	0.079 (0.68)	0.049 (0.43)	-0.136 (-1.11)	0.081 (0.69)	0.081 (0.69)	0.051 (0.45)	-0.137 (-1.12)
LAW	0.078** (2.24)	0.078** (2.24)	0.069** (1.97)	0.017 (0.43)	0.077** (2.23)	0.077** (2.23)	0.068* (1.94)	0.017 (0.44)
LG	0.003** (2.08)	0.003** (2.08)	0.003* (1.68)	0.004*** (2.75)	0.003** (2.07)	0.003** (2.06)	0.003* (1.65)	0.004*** (2.75)
EU	0.287*** (2.22)				0.306** (2.02)			
Non-EU		-0.287** (-2.22)				-0.305** (-2.02)		
MDE			-0.286** (-2.29)				-0.335** (-2.26)	
BIS				1.003*** (2.91)				1.039*** (2.83)
ELECT*EU					-0.063 (-0.24)			
ELECT*NON-EU						0.063 (0.24)		
ELECT*MDE							0.165 (0.62)	
ELECT*BIS								-0.199 (-0.29)
R^2	88.24	88.24	88.25	88.39	88.24	88.24	88.27	88.39
Adjusted R^2	87.42	87.42	87.43	87.57	87.38	87.38	87.41	87.54
F-statistic	108.07	108.72	108.19	109.54	102.59	102.59	102.83	103.99
Prob (F-statistic)	0.000	0.000	0.0000	0.000	0.000	0.000	0.000	0.000
No of Observations	309	309	309	309	309	309	309	309
The Models in Table 5 are estimated using fixed effect regression (with year fixed effects only). GMM estimations could not be run due to near-perfect collinearity of the lag variables with the instrumental variables. NPL = ratio of nonperforming loans to gross loans: the lower the better; ELECT = a binary variable that equal one in an election year and zero in non-election year. CRISIS = a binary variable that equal one in a financial or banking or economic crisis year and zero otherwise. ΔGDP = real								

domestic product growth rate; CC = control of corruption index: the higher the better; PS = political stability / absence of terrorism index: the higher the better; LAW = rule of law index; the higher the better. LG = ratio of credit provided to the private sector by banks as a share of GDP. EU = a binary variable that equal one if the country is a member of the European Union and zero otherwise. Non-EU = a binary variable that equal one if the country is not a member of the European Union and zero otherwise. MDE = a binary variable that equal one if the country is a member of the G7 countries according to the UN's classification. ***, **, * denotes 1%, 5% and 10% significance level.

Table 6

Table 6: Testing the income smoothing and capital management hypothesis during election years						
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)
C	1.913** (2.21)	1.255 (1.39)	-1.896 (2.22)	1.356 (1.48)	0.817 (0.76)	0.814 (0.77)
ELECT	0.172 (1.38)	-0.207 (-1.17)	0.183* (1.60)	-0.215 (-1.18)	-0.918* (-1.91)	-0.486* (-1.70)
NPL	0.436*** (31.24)	0.448 (32.38)	0.437 (31.43)	0.454*** (32.44)	0.449*** (29.13)	0.445*** (29.06)
CRISIS	0.086 (0.58)	0.097 (0.63)	0.089 (0.59)	0.096 (0.61)	0.074 (0.44)	0.169 (1.03)
ΔGDP	0.025 (1.32)	0.024 (1.29)	0.026 (1.33)	0.023 (1.24)	0.022 (1.09)	0.025 (1.26)
PS	-0.104 (-0.42)	-0.007 (-0.03)	-0.116 (-0.48)	-0.015 (-0.06)	-0.078 (-0.29)	-0.235 (-0.86)
CC	-0.417 (-1.36)	-0.104 (-1.53)	-0.397 (-1.32)	-0.498 (-1.59)	-0.545* (-1.65)	-0.369 (-1.09)
LAW	-0.112* (-1.77)	-0.104 (-1.61)	-0.110* (-1.75)	-0.107 (-1.61)	-0.063 (-0.88)	-0.065 (-0.91)
LG	0.002 (0.75)	0.002 (0.82)	0.002 (0.63)	0.002 (0.77)	0.004 (1.28)	0.003 (1.11)
EBTP	0.038 (0.93)					
EBTP2		0.216*** (3.91)				
ROA			0.056 (1.29)			
NIM				0.203*** (3.45)		
ELECT(-1)	-0.053 (-0.53)	-0.417** (-2.35)	-0.036 (-0.36)	-0.435** (-2.35)	-0.331 (-0.76)	-0.362 (-1.41)
ELECT*EBTP	-0.065 (-0.74)					
ELECT*EBTP2		0.151** (2.41)				
ELECT*ROA			-0.091 (-0.96)			
ELECT*NIM				0.158**		

				(2.36)		
ELECTt-1*EBTP	-0.042 (-0.75)					
ELECTt-1*EBTP2		0.152** (2.39)				
ELECTt-1*ROA			-0.067 (-1.05)			
ELECTt-1*NIM				0.163** (2.38)		
CAR					0.038 (1.55)	
CAP						0.073* (1.95)
ELECT*CAR					0.081** (2.28)	
ELECT*CAP						0.094** (2.37)
ELECTt-1*CAR					-0.331 (-0.76)	
ELECTt-1*CAP						0.043 (1.24)
R^2	93.90	94.23	93.95	94.04	93.31	93.49
Adjusted R^2	92.49	92.91	92.56	92.69	91.79	92.00
F-statistic	66.46	71.92	67.82	69.55	61.50	62.57
Prob (F-statistic)	0.000	0.000	0.000	0.000	0.000	0.000
J-statistic						
Prob (J-statistics)						
No of Obs (adjusted)	288	293	291	293	293	290

Models in Table 6 are estimated using fixed effect regression (with country and year fixed effects). GMM estimations could not be run due to near-perfect collinearity of the lag variables with the instrumental variables. NPL = ratio of nonperforming loans to gross loans: the lower the better; ELECT = a binary variable that equal one in an election year and zero in non-election year. CRISIS = a binary variable that equal one in a financial or banking or economic crisis year and zero otherwise. ΔGDP = real domestic product growth rate; CC = control of corruption index: the higher the better; PS = political stability / absence of terrorism index: the higher the better; LAW = rule of law index; the higher the better. LG = ratio of credit provided to the private sector by banks as a share of GDP. LLP = is the one-year lag of the loan loss provisions variable. ELECTt-1 = is the one-year lag of the ELECT variable. EBTP = provisions-adjusted earnings variable (when loan loss provisions are added back to ROA). EBTP2 = provisions-adjusted earnings variable (when loan loss provisions are added back to NIM). CAR = ratio of bank regulatory capital to risk-weighted assets. CAP = ratio of bank capital to total assets. ***, **, * denotes 1%, 5% and 10% significance level.