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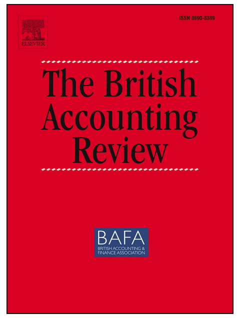

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Income smoothing among European Systemic and Non-Systemic Banks

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Abstract

There is scant research on the financial reporting behaviour of global systemically-important banks (G-SIBs) and non-global systemically-important banks (non-G-SIBs). We examine the link between financial reporting and financial system stability given the understanding that income smoothing is a stability mechanism for banks. We empirically examine whether the way G-SIBs use loan loss provisions (LLPs) to smooth income differ compared to non-G-SIBs and the incentive to do so. We examine 231 European banks and find that income smoothing is pronounced among G-SIBs in the post-crisis period and pronounced among non-G-SIBs in the pre-crisis period. Also, G-SIBs exhibit greater income smoothing when they: (i) have substantial non-performing loans, (ii) are more profitable and meet/exceed minimum regulatory capital ratios (iii) engage in forward-looking loan-loss provisioning and during recessionary periods. The implication of our findings is that capital regulation and abnormal economic fluctuations create incentives for systemic banks to use accounting numbers (loan loss provisions) to smooth income, which also align with the financial system stability objective of bank regulators. Our findings are useful to accounting standard setters in their evaluation of the role of reported accounting numbers for financial system stability, given the current regulatory environment in Europe which focuses on systemic banks.

Keywords: Loan loss provisions; income smoothing; Europe; systemic banks; accounting information; financial reporting

JEL codes: E58, G21, G28, G32, M41

Income Smoothing among European Systemic and Non-systemic Banks

1. Introduction

Systemic banks (also known as G-SIBs or SIFIs) are defined as “financial institutions whose distress or disorderly failure, because of their size, complexity and systemic interconnectedness, would cause significant disruption to the wider financial system and economic activity” (FSB, Policy measures to address SIFIs, 11/2011). Systemic banks (also known as G-SIBs or SIFIs) are defined as “financial institutions whose distress or disorderly failure, because of their size, complexity and systemic interconnectedness, would cause significant disruption to the wider financial system and economic activity” (FSB, Policy measures to address SIFIs, 11/2011). The severity of the 2008 global financial crisis put the “systemic” or “too big to fail” issue to the forefront due to the potentially disruptive impact on financial stability of the failure of a large financial institution which was highlighted by the collapse of Lehman Brothers (Mesnard et al, 2017)[1]. At global level, regulators and policy makers around the world agreed quickly that the issue of financial firms perceived as too big, too complex or too interconnected to fail should become a regulatory priority; the Financial Stability Board (FSB) proposed possible measures to address the ‘too big to fail’ problems associated with systemically important financial institutions and published an initial group of global systemically important banks (G-SIBs), using a methodology developed by the Basel Committee on Banking Supervision[2] (Mesnard et al, 2017). At bank level, banks take some measures to achieve bank stability, and one of such measures is stability through financial reporting. One financial reporting property that align with stability objectives is earnings management.

Earnings management can have positive or negative effects for financial system stability, and this effect depends on the type of earnings management employed, which also depends on the regulatory classification of firms used by regulators to place stricter regulatory oversight on some firms compared to other firms. Income smoothing is a type of earnings management which can have positive effects for financial system stability if it helps banks remain stable by reducing earnings volatility or could have negative effects by contributing to systemic crash and distress risk (Bushman and Williams, 2015; Ma and Song, 2016). After the 2007 global financial crisis, a joint consultation with the Financial Stability Board (FSB) and the Basel Committee for Banking Supervision (BCBS), using a common methodology[3], produced a list of global systemic banks (G-SIBs) and non-global systemic banks (non-G-SIBs) to identify financial institutions that pose the greatest risk to the financial system and whose systemic properties exacerbated the financial crisis during their near collapse in 2008.

Brunnermeier et al (2009) demonstrate that lax regulation and supervision during the US housing boom between 2004 and 2005 which also spread into Asia and Europe provided incentives for banks to become systemic as they took excessive risks in mortgage-backed securitisation which over time amplified their systemic risk exposure to the financial system at the time. Therefore, the joint FSB-BCBS list for systemic banks is expected to capture banks that were systemic before the 2007/2008 global financial crisis. However, there is little

[1] http://www.europarl.europa.eu/RegData/etudes/BRIE/2016/574406/IPOL_BRI(2016)574406_EN.pdf
[2] http://www.fsb.org/2011/11/r_111104bb/
[3] The FSB-BCBS methodology for G-SIBs is available here: http://www.bis.org/bcbs/publ/d296.pdf

information available about the financial reporting properties of systemic firms compared to non-systemic firms. More specifically, it is unclear whether the income smoothing or earnings management behaviour of systemic (G-SIBs) and non-systemic (non-G-SIBs) banks have positive or negative effects for financial system stability, particularly when loan loss provisions is used to smooth income. Due to these concerns, we seek to understand the effect of systemic banks' financial reporting practices for financial system stability while taking into account banks' risk-taking decisions affecting their overall loan potfolio - because banks' systemic risk exposure is not independent of their risk-taking decisions. Hence, For the purpose of this paper, we take advantage of the systemic classification developed by the FSB and BCBS, which allows us to focus on global systemic banks (G-SIBs) compared to non-global systemic banks (non-GSIBs), where systemic banks (or G-SIBs) are banks that have the highest systemic risk contribution to the financial system compared to non-systemic banks (or non-G-SIBs).

Loan-loss provisions (LLPs) are important accruals[4] for banks because they convey information about future deterioration of the quality of bank loan portfolio. However, accounting standard setters have paid less attention to the role of loan loss provision, as an accounting number for financial system stability. This has become more relevant for the current debate to replace the backward-looking incurred loss provisioning model with a more forward looking provisioning model in 2018 to ensure financial system stability (Andreou et al, 2017; Gaston and Song, 2014; Marton and Runesson, 2017). However, due to the discretion that bank managers have in estimating LLPs, there are significant concerns that bank managers can exploit the provisioning policy of banks to pursue goals that are different from the intended purpose of LLPs which is to estimate expected credit losses, and such goals may include: the need to reduce crash risk (Andreou et al, 2017), to smooth income (Leventis et al, 2011), to manage regulatory capital (Ahmed et al, 1999), and the need to signal information about firms' future prospects (Kanagaretnam et al, 2005). Our study focus on the bank income smoothing debate (Lobo and Yang, 2001; Kanagaretnam et al, 2003; Leventis et al, 2011) in relation to two bank categories (G-SIBs and non-G-SIBs) that have dominated the scene of macro prudential and systemic banking regulation in Europe for almost a decade now. So far, no study has examined the issues relating to whether G-SIBs use accounting numbers (e.g. LLPs) to smooth income and whether the motivation to do differ significantly compared to non-G-SIBs in Europe.

In Europe, G-SIBs are banks that have the highest systemic risk contribution to the entire financial system (Markose, 2012; Markose, Giansante and Shaghaghi, 2012), requiring bank supervisors to ensure that significant regulatory oversight is in place to monitor the risky activities of G-SIBs compared to non-G-SIBs particularly in their derivatives and securitisation activities which was singled out to be central to the 2008 global financial crisis. The financial crisis revealed that G-SIBs became systemically important long before they were classified as 'systemic' institutions by banking regulators in 2011 (Brunnermeier et al, 2009). Subsequently, G-SIBs became the subject of intense debate about whether insufficient bank capital, excessive risk-taking, poor loan-loss provisioning policies or perverse regulatory incentives contributed to the near collapse of some G-SIBs during the global financial crisis (Acharya, 2009; Gorton et al, 2010; Acharya and Yorulmazer, 2007). Yet, there is a paucity of research addressing the financial reporting behaviour of systemic banks (or G-SIBs) compared to

[4] Accrual is a non-cash item in the asset-side or liability-side of banks' balance sheet. Loan loss provisions is a non-cash asset item.

non-systemic banks (or non-G-SIBs) in the banking literature. We contribute to the financial reporting literature by focusing on the income smoothing behaviour of G-SIBs and non-G-SIBs.

Recently, the debate for financial system stability has focused on the stability of systemic banks whose failure (or instability) can have serious consequences for the stability of the banking system, therefore, requiring substantial/excessive scrutiny of the performance indicators of systemic banks from a systemic regulation perspective (Drehmann and Tarashev, 2013; Tabak et al, 2013; Black et al, 2016) which therefore leads to the question about whether G-SIBs smooth income to hide their risks before, during and after the financial crisis compared to non-G-SIBs to make their risks less visible to bank supervisors in order to avoid excessive scrutiny from bank supervisors, which further leads to questions about specific accounting numbers that might be used to smooth reported earnings. We focus on LLPs because prior studies identify LLPs as a tool that banks use to signal information about future firms' prospects, minimise crash risk or to smooth income although with mixed results in the literature (Andreou et al, 2017; Liu and Ryan, 1995; Kanagaretnam et al, 2003; Shrieves and Dahl, 2003; Fonseca and Gonzalez, 2008; Bushman and Williams, 2012; El Sood, 2012; Curcio and Hasan, 2015). From a different perspective, income or earnings stability may be considered to be an indicator of firm stability (Brunnermeier et al, 2009), and income smoothing by banks can contribute to financial system stability where the stability of each bank that report stable (or smooth) profits collectively translate to the stability of the entire banking/financial system. In this paper, we argue that if G-SIBs face pressure to align their behaviour to the goals of financial system stability required by bank supervisors, G-SIBs will influence their financial reporting to make bank earnings appear stable over time to improve regulators' perception about their performance and stability. To date, it is not clear whether and how G-SIBs smooth reported earnings and it is also not clear whether they use LLPs to smooth income relative to non-G-SIBs. We use a sample of 231 European banks divided into G-SIBs and non-GISBs, and we find that systemic banks (GSIBs) use accounting numbers (loan loss provisions) to smooth income which also align with the financial system stability objective of bank regulators. We also find that G-SIBs use LLPs to smooth income when they expect losses and during the post-financial crisis period while non-G-SIBs use LLPs to smooth income in the pre-crisis period.

Our contribution to the literature is as follows. One, we contribute to the literature that explore whether classificatory regulation motivates the affected firms to distort their financial reporting to meet specific reporting objectives underlying the regulatory classification (e.g. Kilic et al (2012)). We examine whether the G-SIB and non-G-SIB regulatory classification create additional incentives for the affected banks to use accounting numbers to smooth income. Two, we contribute to the literature exploring the relationship between bank financial reporting properties and financial system stability by analysing the link if any between provisions-based income smoothing and financial system stability focussing on global systemically-important banks. Three, by controlling for macroeconomic fluctuation, we contribute to the procyclicality literature that examine how procyclical provisioning reinforces the current state of the economy. Our analyses shed some light to how the provisioning of G-SIBs might exacerbate macroeconomic procyclicality and to understand whether forward-looking provisioning by G-SIBs is a step in the right direction to mitigate the procyclicalty of bank provisions for systemic banks. Finally, from a policy perspective, our study provides insights to global bank regulators who want to understand how G-SIBs attempt to (i) reduce regulatory pressure from bank supervisors

(ii) avoid excessive scrutiny of its activities particularly bank profits, and (iii) how G-SIBs try to hide their risks by appearing stable over time.

Section 2 discusses the conceptual framework and literature. Section 3 develops the hypotheses. Section 4 describes our data and methodology. Section 5 presents and discusses the results testing the income smoothing hypothesis and transient incentives to smooth income. Section 6 concludes.

2. Conceptual Framework and Literature

2.1 Theoretical Literature

2.1.1. Regulating Systemic Banks

In this section, we use the term G-SIBs (or systemic banks) and non-G-SIB (and non-systemic banks) interchangeably. We discuss G-SIBs and non-G-SIBs in the context of micro- and macro- prudential banking regulation. Micro prudential bank regulation is concerned with improving the behaviour and risk management practices of individual banks including G-SIBs and non-G-SIBs with the expectation that the stability of individual banks would translate to the stability of the financial system as a whole (Brunnermeier et al, 2009; Dell'ariccia et al, 2008; Gorton et al, 2010). Before the 2008 financial crisis in the early 2000s, bank regulation in many countries focused on micro prudential regulation which in practice had some justification in the theory of bank regulation. Today, there is a shift towards macro prudential banking regulation which partly entails imposing strict supervisory requirements for systemic banks because they pose the greatest risk to the stability of global financial system from a macro prudential regulation perspective (Galati et al, 2013). Recently, there are arguments about the need to combine micro and macro prudential regulation which would further impose strict supervisory requirements on systemic banks (G-SIBs) both at the micro and macro levels (Galati et al, 2013; Goodhart, 2015). Excessive focus on systemic banks by the complex bank regulatory and supervisory infrastructure (i.e, the SEC, IFRS, BCSC and FSB) may compel G-SIBs to change their behaviour to align with bank supervisors' expectations to create the impression that they are behaving prudently while also achieving their own opportunistic objectives. One technique that can help G-SIBs achieve these two objectives is to use accounting numbers to smooth bank reported earnings because such behaviour is consistent with financial system stability objectives while at the same time increasing the opacity of the reported earnings of G-SIBs. Moreover, if bank supervisors view income smoothing by individual banks as each bank's contribution to financial system stability, the strict supervision of G-SIBs compared to non-G-SIBs will not be aimed at limiting the way G-SIBs use LLPs to smooth income, thus, providing additional incentives for G-SIBs to smooth income.

2.1.2. G-SIBs and Non-G-SIBs

The Basel Committee on Banking Supervision (BCBS) developed a methodology to determine the systemic importance of individual banks based on five categories with equal weights which are: size, interconnectedness, complexity, substitutability and cross-jurisdictional activity. In Europe, banks are required to publish information for each category which is used to determine if a bank is systemic or not. "Size" conveys the idea that the systemic importance of a bank is related to the volume of services it provides, mainly total exposures including off-balance sheet items. This indicator is supported by Huang et al (2012) and Lopez-Espinosa et al (2012). "Interconnectedness" conveys the idea that the systemic importance of a bank is related to banks' linkages with other financial institutions. This is also supported by Allen and Gale (2000) and Freixas et al (2000). "Complexity" conveys the idea that the systemic importance of a bank is associated with the complexity and opacity of the banking operations of the bank. This is supported by Flannery et al (2013). "Substitutability", in simple terms, conveys the idea that the systemic importance of a bank is associated with the lack of readily available substitutes for the services the bank provides to the economy while "cross-jurisdictional activity" conveys the idea that the systemic importance of a bank is related to the extent to which the bank's operations spread across several geographical area. Finally, banks that do not fall into these five categories are considered to be global non-systemic banks (non-G-SIBs) for the purpose of this study. A non-G-SIB may be systemic to the financial system of a domestic country but not systemic at a global level[5] (See BCBS 2013, 2014). However, large international banks are not the only systemic banks in Europe, and this has been the case in several European countries in recent years since 2014.

In Europe, G-SIBs are banks that have the highest systemic risk contribution to the financial system compared to non-G-SIBs, requiring bank supervisors to ensure that significant regulatory oversight is in place to monitor the risky activities of G-SIBs compared to non-G-SIBs particularly in their derivatives and securitisation activities which was singled out to be central to the 2008 global financial crisis. Prior to the financial crisis, banks engaged extensively in securitisation activities that gave rise to interconnected financial obligations and claims among banks. Over time, these claims became concentrated among few banks and led to the emergence of few, dominant and highly interconnected banking institutions connected in a way that the failure of a dominant banking institution could lead to the failure of other banks connected to it in the financial system (Allen and Gale 2000). These banks became systemically important long before they were officially classified as 'systemic' by banking regulators in 2011. During the crisis, European bank supervisors intervened to rescue systemic banks now referred to as G-SIBs, and subsequently increased the supervision and monitoring of the securitisation activities of G-SIBs. However, excessive monitoring/scrutiny of the securitisation activities of G-SIBs aimed at discouraging G-SIBs from using derivatives to manipulate earnings may encourage them to rely on the use of loan-loss provisions estimates to manipulate reported earnings which can be achieved by smoothing earnings over time. Kilic et al (2012) observe that this was the case for US banks after the adoption of SFAS 133. Moreover, because there is currently no separate IFRS accounting disclosure standard for G-SIBs relative to non-G-SIBs which should place higher disclosure requirements for G-SIBs, G-SIBs may have incentives to opportunistically manage their earnings under the current accounting regulatory framework. Also, Signalling theory can provide an alternative explanation (Kanagaretnam et al, 2005; Leventis et al, 2012), that strong banks (or G-SIBs) may keep fewer provisions to signal their superior ability to use other risk management techniques to hedge against credit losses so that loan loss provisions are relatively lower (Nicolo and Pelizzon, 2008), which can then be used to smooth (or increase) income; alternatively, riskier banks may report higher loan loss provisions as a signalling device to communicate confidence and safety, and their ability to anticipate credit risk (Leventis et al, 2012).

[5] It is important to stress that, recently, large international banks are not the only systemic banks in Europe, and this is the case in several countries in the post-2014 period.

2.1.3. Earnings Management to Avoid Scrutiny among Large Firms

To the extent that G-SIBs (or systemic banks) are large firms, the theoretical earnings management literature demonstrate that larger firms tend to smooth income or manage earnings to a greater extent compared to smaller firms. Alchian and Kessel (1962) and Zimmerman (1983) argue that the reported earnings of large firms are more politically sensitive than the reported earnings of smaller firms and managers of larger firms will prefer to use accounting procedures that decrease high earnings for fear of political and/or regulatory scrutiny of bank earnings. Nelson (2002) show that income smoothing behaviour among large firms may persist if auditors overlook the earnings management practices of larger clients because of the large fee they receive from larger clients. Burgstahler and Dichev (1997) examine the impact of earnings management on the negative earnings of 300 firms and find that large firms and small ones manage their earnings in order to avoid small losses or small profits decline. DeGeorge et al (1999) find that large companies managed earnings to avoid reporting negative earnings. Barton and Simko (2002) show that larger companies face more pressure to meet the analysts' expectations. Ching et al (2002) investigate whether unrestricted current accruals predict the returns and earnings performance of firms and find that larger firms manipulate current accruals to overstate earnings to a greater extent than smaller firms. Kilic et al (2012) show that US banks smooth income to avoid regulatory scrutiny. They examine whether the strict recognition requirements of SFAS 133 which reduced US banks' ability to smooth earnings through the use of derivatives encouraged US banks to rely on LLPs to smooth reported earnings rather than rely on derivatives. They find evidence that US banks use LLPs to smooth earnings when accounting disclosure regulation made it difficult to use derivatives to smooth bank earnings. Taken together, because G-SIBs are large firms, the above studies suggest a good case for earnings management among G-SIBs due to their size and their need to avoid excessive scrutiny although this has not been tested for G-SIBs in the empirical literature. Therefore, in this paper, we focus on bank income smoothing, a type of bank earnings management behaviour.

2.2. Income Smoothing and Bank Provisions

While there is substantial evidence that banks use LLPs to smooth income in the banking literature (Ahmed et al, 1999; Shrieves and Dahl, 2003; Lobo and Yang, 2001; Kanagaretnam et al, 2003), the literature remain silent on the income smoothing (or earnings management) practices of G-SIBs relative to non-G-SIBs. Among European studies, Leventis et al (2011) investigate the impact of IFRS disclosure regulation on bank income smoothing via LLPs among 91 listed EU banks from 1999 to 2008 and find that risky banks use LLPs to smooth income more aggressively than less risky banks. Leventis et al (2011)'s classification of risky banks was not based on banks' systemic importance to the global banking system. Using stock price data, Andreou et al (2017) show that conditional conservatism in loan loss provisioning reduces crash risk for small banks during periods of credit contraction and boom but not for large banks. Curcio and Hasan (2015) investigate income smoothing among Euro Area and non-Euro Area credit institutions and find evidence for income smoothing via provisions. Skala (2015) investigates income smoothing and procyclicality among Central European banks from 2004 to 2012 and find evidence for income smoothing. Perez, Salas, and Saurina (2008) examine the use of LLPs for income smoothing and capital management among Spanish banks and find that Spanish banks use LLPs to smooth income but not to manage capital. Curcio et al (2017) investigate the discretionary provisioning behaviour of Euro Area banks during the financial crisis period at a time when banks were subject to stricter supervision, namely the EBA 2010 and 2011 stress test exercise. They find that Euro Area banks subject to EBA stress tests had greater incentives to use loan loss provisions to smooth income only for the 2011 EBA exercise which required the disclosure of large set of information. Bonin and Kosak (2013) investigate LLP practices among banks in emerging European countries from 1997 to 2010 and find evidence for income smoothing and macroeconomic procyclicality. Bouvatier et al (2014) also find reduced income smoothing behaviour among banks in countries with stronger supervisory regimes. Also, reduced income smoothing and greater accounting conservatism can reflect higher transparency in financial reporting, to support this claim, Bhattacharya et al (2003) show that income smoothing is a measure of earnings transparency because artificially smoothed earnings may fail to depict the swings in underlying firm performance which increases earnings opacity while earnings conservatism results from the tendency of managers to decrease reported earnings numbers. In fact, Manganaris et al (2017) did not find evidence for conservatism during the first years of mandatory IFRS adoption among European banks but found evidence for greater conservatism after the 2008 crisis. Jointly, these studies did not examine systemic and non-systemic banks in Europe. In this study, we examine the case of systemic (G-SIBs) and non-systemic (non-G-SIBs) in Europe.

3. Hypothesis Development

To develop the hypotheses, first we follow the income smoothing hypothesis which argues that banks would decrease LLPs to increase low earnings and increase LLPs to reduce high earnings (Bhat, 1996; Ahmed et al, 1999; Lobo and Yang, 2001; Shrieves and Dahl, 2003). We refine the income smoothing hypothesis and predict that European G-SIBs would use LLPs to smooth income possibly to (i) align their behaviour with the stability objective of bank supervisors, (ii) to hide their risks to make it less visible (iii) or to avoid scrutiny of excessive bank profits (Zimmerman, 1983), compared to non-G-SIBs. Therefore, in the first hypothesis, we predict that G-SIBs use loan-loss provisions to smooth income to a greater extent than non-G-SIBs. However, we might expect reduced income smoothing behaviour among G-SIBs - (i) have more sophisticated internal control system that discourage earnings manipulation compared to non-G-SIBs) (ii) have efficient corporate governance systems (Leventis and Dimitropoulos, 2012) and (iii) if they seek to protect their reputation to avoid being accused of fraudulent behaviour in the community (see, Warfield et al, 1995).

H1: G-SIBs use loan-loss provisions to smooth income to a greater extent than non-G-SIBs.[6]

Next, we refine the income smoothing hypothesis and predict that the incentive to use LLPs to smooth reported earnings may depend on the size/distribution of bank earnings that is, high earnings, non-negative earnings and negative earnings. Balbao et al (2013) find that US banks have incentives to smooth non-negative earnings and substantial earnings and conclude that the use of LLPs to smooth income may be targeted at abnormal pattern in earnings distribution. El Sood (2012) finds that US banks use LLPs to smooth income to lower earnings when they are more profitable, that is, when they have high earnings. Accordingly, we predict that the incentive to use LLPs to smooth reported earnings may depend on the size/distribution of bank earnings which includes high earnings, non-negative earnings and negative earnings. However, we do not have a definite prediction for G-SIBs and non-G-SIBs, therefore, we hypothesize that :

[6] However, we might expect reduced income smoothing behaviour among G-SIBs if larger firms (for example, G-SIBs) have more sophisticated internal control system that discourage earnings manipulation, compared to smaller firms (for example, non-G-SIBs) and if they seek to protect their reputation to avoid being accused for fraudulent behaviour in the community (see, Warfield et al, 1995).

H2: the difference in the income smoothing behaviour of G-SIBs and non-G-SIBs depends on the earnings distribution or earnings size.

Finally, we refine the income smoothing hypothesis and predict that banks' incentive to smooth earnings depend on transient states of the economic cycle. Liu and Ryan (2006) show that banks use loan loss provision to smooth income during economic booms. They observe that banks increase LLPs to lower high earnings during the 1990 economic boom. In contrast, El Sood (2012) show that banks use loan loss provision to smooth income when they enter recessionary periods. These two findings are supported by evidence for the procyclical behaviour of bank provisions. For instance, Laeven and Majnoni (2003) demonstrate that banks tend to overstate LLPs during recessionary periods and keep fewer LLPs during economic boom periods while Bikker and Metzemakers (2005) find that banks in OECD countries delay LLPs to smooth bank earnings upwards during recessionary periods so that earnings do not become too low during the recessionary period.

Moreover, the effect of fluctuating economic conditions on bank income smoothing may be dampened by several factors such as accounting rules, conservatism, stock market fluctuations, bank size, etc. For instance, Andreou et al (2017) find that smaller banks that follow conditional conservatism in their loan loss provisioning treatment have reduced crash risk during periods of credit contraction and boom compared to large banks, implying that large banks are less conservative (or aggressive) in their loan loss provisioning. Marton and Runesson (2017) observe that bank loan loss provisions in IFRS bank years predict future credit losses to a lesser extent than in local GAAP bank years, implying that the incurred loss model reduced the timeliness of bank provisions. Leventis et al (2011) show that income smoothing is reduced during mandatory IFRS periods, although their regression results show that loan loss provisions are procyclical with fluctuation economic conditions while Pool et al (2015) show that loan loss provisioning decreases during expansionary credit booms. Olszak et al (2017) show that the provisions of large, publicly-traded and commercial banks are more procyclical with fluctuating economic conditions but LLP procyclicality is weakened by restrictive capital standards and better investor protection. Generally, we can expect recessionary and expansionary trends to have similar impact on bank profitability regardless of whether the bank is systemic or non-systemic, however, the way European G-SIBs and non-G-SIBs might use LLPs to smooth earnings during booms and recessions (and the financial crisis) remain unknown or unclear. We predict that the income smoothing behaviour of G-SIBs and non-G-SIBs is influenced fluctuating economic conditions. Therefore, we hypothesize that:

H3a: G-SIBs smooth income during economic boom than non-G-SIBs, and vice versa

H3b: G-SIBs smooth income during recessions (and the financial crisis[7]) than non-G-SIBs, and vice versa

4. Data and Methodology

4.1. Data

The sample consists of European banks for the period 2004 to 2013 from 16 European countries. The countries include: United Kingdom, Denmark, Finland, Ireland, Greece, Portugal, Belgium, Austria, Italy, France, Luxemburg, Spain, Netherland, Germany, Sweden and Norway. Bank income statement and balance sheet data

[7] El Sood (2012) finds that LLPs are used extensively by US banks to smooth income during the financial crisis. To date, the impact of the post-financial crisis banking environment on the income smoothing behaviour of banks is not clear in the bank income smoothing literature partly because the period of analyses in most studies do not focus on post-financial crisis period to a large extent

were collected from Bankscope database. We focus on the European context which allows us to control for differences in the accounting for loan-loss provisions since European banks adopt uniform IFRS procedure in the determination of LLP estimates. We use the Basel Committee for Banking Supervision (BCBS) and Financial Stability Board (FSB)'s 2014 classification of G-SIBs which allows us to identify banks that are G-SIBs and banks that are non-G-SIBs in the region (i.e., banks not included in the FSB and BCBS list).[8]

Data for real gross domestic product growth rate was collected from World Economic Forum. To be included in the G-SIB sub-sample, the European bank must be listed as a Global Systemically Important Bank (G-SIB) as at 2014 in the joint statement issued by the Financial Stability Board (FSB) and the Basel Committee for Banking Supervision (BCBS)[9] given the understanding that the G-SIBs were already systemic long before the 2008 financial crisis (FSF, 2009) and until 2013. Banks that were not listed as a G-SIB are considered to be non-G-SIBs. Also, the G-SIBs and non-G-SIBs must be domiciled in a European country sample, therefore, G-SIBs in the BCBS and FSB's list that are not fully operational in European countries are excluded from the analyses. Secondly, most G-SIBs in our sample for each country have full time series data for crucial variables. Moreover, the number of non-G-SIBs in the sample is relatively larger than G-SIB, and some non-G-SIBs have full reporting data while others do not have full data implying an unbalanced panel sample. We include G-SIBs and non-G-SIBs that have time series data for at least (t-1) sample period, where t is the sample period (2004-2013) in order to control for the quality of financial reporting. The (t-1) criteria allow us to avoid restricting the sample to banks that had full reporting year-data for the full sample period to minimise survivorship bias in the non-G-SIBs sub-sample. Thirdly, the data is trimmed to eliminate outliers at the top and bottom at 99% and 1%, respectively. Finally, we eliminated 2008 bank-year observations to control for the impact of the financial crisis on bank balance sheet. This leads to a final sample of 231 banks consisting of 41 G-SIBs and 190 non-G-SIBs. See Appendix for distribution of G-SIBs and non-G-SIBs across countries.

4.2. Methodology

The multivariate model we employ to test the income smoothing hypothesis is similar to Kilic et al (2012), Bushman and Williams (2012) and Curcio and Hasan (2015), and is expressed as:

$$LLPit = \beta 1 + \beta 2EBTPit + \beta i\sum Controls + eit. \qquad Eq\ (1)$$

The expanded model is stated below:

$$LLPit = \beta 0 + \beta 1EBTPit + \beta 2CARit + \beta 3NPLit + \beta 4LOANit + \beta 5SIZEit + \beta 6\Delta GDPjt + eit. \qquad Eq\ (2)$$

Where LLP is the ratio of loan-loss provisions to total asset for bank i at year t while EBTP is the ratio of earnings before tax and loan-loss provisions to total assets. Laeven and Majnoni (2003), Bikker and Metzemakers (2005), Leventis et al (2011) and Bouvatier et al (2014) use LLP and EBPT, and deflated the two variables by total assets. EBTP is derived by adding back loan-loss provisions to profit before tax.

For the first hypothesis, a significant and positive sign for EBTP coefficient is predicted as evidence for income smoothing. Also, we test whether European G-SIBs and non-G-SIBs use LLPs to smooth income when they

[8] The BCBS and FSB are two bank supervisory bodies that worked together to develop G-SIB classification of banks in an attempt to address the systemic risk of the financial system.

[9] For instance, if HSBC is listed as a G-SIB and is located in the UK, we assign this bank to the G-SIB category. If a bank is not listed as a G-SIB and is located in the UK, we assign this bank to the G-SIB category. This is the approach we use for all 16 European countries.

expect substantial earnings. We use two dummy variables as proxies for substantial earnings: POS and HIGH. 'POS' take the value of one if EBTP is positive and zero otherwise reflecting periods when banks have non-negative earnings while 'HIGH' take the value of 1 if EBTP is above-the-median EBTP and zero otherwise reflecting periods when banks are more profitable. This is in line with Liu and Ryan (2006) and El Sood (2012). Additionally, we test whether banks use LLPs to smooth income when they expect losses (i.e. negative earnings). We introduce 'NEG' dummy variable that takes the value of one if EBTP is negative and zero otherwise. NEG is interacted with EBTP to detect whether LLP-based income smoothing is significantly associated with bank losses. Therefore, for the second hypothesis, a significant and positive sign for POS*EBTP and HIGH*EBTP coefficient is predicted as evidence for income smoothing when banks are more profitable.

Following prior literature, we employ control variables to isolate the non-discretionary components of LLP from its discretionary component (Ahmed et al, 1999; Lobo and Yang, 2001). Our control variables include NPL, LOAN, CAR, SIZE and ∆GDP. NPL is the ratio of non-performing loans to gross loan ratio which captures specific provisions that banks set aside for actual loan losses (Beaver and Engel, 1996). We expect banks to increase specific provisions when they expect higher actual loan losses, implying a positive sign for the NPL coefficient. Also, we test whether G-SIBs and non-G-SIBs use LLPs to smooth income when they have double-digit NPLs in order to detect whether the incentive to use LLPs to smooth income is driven by the magnitude of NPLs. To capture this, we introduce 'NPLD' dummy variable that takes the value of one if NPL ratio is a double-digit number and zero otherwise. NPLD is then interacted with EBTP to detect whether LLP-based income smoothing is more pronounced when both banks have significant NPLs. CAR is the ratio of Tier 1 capital (non-adjusted for LLPs) to risk weighted assets and controls for banks' incentive to use LLPs to manage regulatory capital (Ahmed et al, 1999). We expect banks to keep higher LLPs when they have low CAR to compensate for their low regulatory capital, implying a negative sign for CAR coefficient. Also, we test whether banks with sufficient regulatory capital ratios exhibit greater income smoothing. To capture this, we introduce 'WC' dummy variable that takes the value of one if CAR is at least 8% and zero otherwise. 'WC' is then interacted with EBTP to detect whether income smoothing via LLP is pronounced among banks with sufficient regulatory capital. LOAN is loan growth or change in outstanding loans and controls for bank provisioning in response to contemporaneous credit risk arising from increased bank lending (Laeven and Majnoni, 2003; Bikker and Metzemakers, 2005). SIZE variable is included to control for bank provisioning that is driven by size considerations. Anandarajan et al (2003) argue that larger banks may keep higher LLPs to compensate for the risks associated with their high level of business activities. To measure size, we take the natural logarithm of total assets. With respect to bank size, we also test whether income smoothing via LLP is more pronounced among larger banks. To capture this, we use a dummy variable 'BIG' that takes the value of one if bank size is above-the-median bank size and zero otherwise. 'BIG' variable is then interacted with EBTP to detect whether larger banks exhibit greater income smoothing via LLP. ∆GDP is real gross domestic product growth rate and controls for bank provisioning that depend on the state of the economy. LLPs are often predicted to be higher during recessionary periods and relatively lower during economic upturns, implying a negative relationship between ∆GDP and LLP (Laeven and Majnoni, 2003). With respect to ∆GDP, we also test whether banks (including G-SIBs and non-G-SIBs) use LLPs to smooth income when they are going through economic downturns or booms. We introduce 'REC' dummy variable that takes the value of one if ∆GDP is negative and zero otherwise, reflecting periods of economic downturns. Also, we introduce the 'BOOM' dummy variable that takes the value of one if ΔGDP is above-the-median ΔGDP and zero otherwise, reflecting periods of economic boom.

The expanded model with the interaction terms is presented in Eq (3) below. The presence of multiple binary variables in the Eq (3) requires the use separate regression models to test the interaction effects.

$$\begin{aligned} LLPit = {} & \beta 0 + \beta 1EBTPit + \beta 2CARit + \beta 3NPLit + \beta 4LOANit + \beta 5SIZEit + \beta 6\Delta GDPjt \\ & + \beta 7POSit + \beta 8POS * EBTPit + \beta 9HIGHit + \beta 10HIGH * EBTPit + \beta 11NEGit \\ & + \beta 12NEG * EBTPit + \beta 13WCit + \beta 14WC * EBTPit + \beta 15BIGit + \beta 16BIG \\ & * EBTPit + \beta 17NPLDit + \beta 18NPLD * EBTPit + eit. \qquad Eq\,(3) \end{aligned}$$

Following the approach of Laeven and Majnoni (2003) and Fonseca and Gonzalez (2008), the model is estimated using the GMM first-difference dynamic panel estimator based on Arellano and Bond (1991).

The Arellano and Bond (1991) GMM first-difference estimator addresses the following econometric issues. One, the presence of unobserved bank-specific effect which is eliminated by taking first-difference of all variables; two, the autoregressive nature of bank provisioning, that is, the need to use a lagged dependent variables model to capture dynamic adjustments to bank provisions (Bikker and Metzemakers (2005). Consistent with Bikker and Metzemakers (2005), we introduce the lagged dependent variable to control for banks' dynamic adjustment to loan loss provisions in anticipation of expected loss on bank loan portfolio; three, the likely endogeneity of the explanatory variables. We also use the OLS estimator to observe whether the result is sensitive to alternative econometric estimation. We report the Sarjan (J) Hansen test for the adequacy of instruments in the GMM estimation and also report the m1 and m2 GMM test for first-order and second-order serial correlation.

5. Results

5.1. Descriptive Statistics and Correlation

5.1.1. Full & Sub-Samples

Table 1.1 provides the summary of the descriptive statistics for the full sample, G-SIB and non-G-SIB samples for the 2004 to 2013 period. The mean ratio of LLPs is 0.4%, 0.3% and 0.4% for the full sample, G-SIBs and non-G-SIBs respectively. The relatively low LLPs observed for G-SIBs suggest that G-SIBs keep fewer provisions and do not rely solely on LLPs as a credit risk management tool. On average, EBTP for the full sample is 0.9% and is 0.9% for G-SIBs and 0.8% for non-G-SIBs implying that G-SIBs are marginally more profitable than non-G-SIBs in Europe. NPLs are, on average, 4.53% of gross loans and are lower for G-SIBs at 3.46% and higher for non-G-SIBs at 4.79%, implying that G-SIBs have better credit quality than non-G-SIBs. With regard to CAR, we expect banks with low NPLs to have less regulatory capital for credit risk. Unsurprisingly, G-SIBs report lower CAR (10.48%) compared to non-G-SIBs (11.18%). SIZE is 19.59 for G-SIBs and 18.16 for non-G-SIBs and confirms that G-SIBs are larger than non-G-SIBs and their large size contribute to their systemic importance to the global banking system.

Furthermore, the statistical significance of the difference of means for each bank-level variable reveal some differences between G-SIBs and non-G-SIBs. The mean difference for the SIZE variable is positive and statistically significant at the 1 per cent level, and shows that systemic banks are significantly larger than non-systemic bank, and explains why the FSB-BCBS consider bank size (total assets) as a key determinant (or measure) of systemic risk. Also, the NPL variable reports a negative mean difference and is significant, and show that non-systemic banks have higher non-performing loans than systemic banks. This suggests that systemic banks have superior credit risk management systems to effectively mitigate nonperforming loans to a greater extent than non-systemic banks. Furthermore, banks with fewer nonperforming loans would keep fewer regulatory capital for loan losses, and this explains the negative and signficant mean difference for the CAR variable for G-SIBs, suggesting that systemic banks had fewer regulatory capital durng the period of analysis. Finally, the mean differences remain robust to alterntative significance test for difference of means.

Table 1.1. Descriptive Statistics

	Statistics	LLP	NPL	LOAN	SIZE	CAR	EBTP	ΔGDP	# Banks
Full Sample	Mean	0004	4.53	5.34	18.40	11.05	0.009	1.11	231
G-SIBs	Mean (i)	0.003	3.46	4.38	19.59	10.48	0.009	1.28	41
Non G-SIBs	Mean (ii)	0.004	4.79	5.55	18.16	11.18	0.008	1.07	190
Diff of Means	(iii)=(i)-(ii)	-0.001*	-1.33***	-1.17	1.43***	-0.70**	0.001	0.21	
T-test		-1.835	-3.64	-1.106	18.72	-2.119	0.915		
Sig (p-value)		0.067	0.000	0.269	0.000	0.034	0.359		
Other tests:									
Anova F-test		3.368	13.27	1.224	350.25	4.489	0.839		
Sig (p-value)		0.064	0.000	0.269	0.000	0.034	0.359		
Welch F-test		7.464	28.34	1.083	240.15	9.219	1.331		
Sig (p-value)		0.006	0.000	0.299	0.000	0.003	0.249		
Full Sample	Median	0.002	2.90	4.26	18.09	10.00	0.007	1.66	
	Maximum	0.134	44.86	96.83	22.06	50.76	0.091	6.46	
	Minimum	-0.011	0.00	-90.53	14.41	-6.10	-0.101	-8.86	
	Standard Deviation	0.008	5.39	16.73	1.404	4.819	0.009	0.008	
	Observation	1891	1470	1714	1920	1458	1891	2079	

*Diff of Means = Difference of Means *Sig = significance

The correlation matrix for the full sample, G-SIBs and non-G-SIBs are reported in Table 1.2, 1.3 and 1.4 respectively. LLP and EBTP are negatively correlated in Table 1.2. In Table 1.3 LLP and EBTP are significant and positively correlated for G-SIBs and are negatively correlated for non-G-SIBs in Table 1.4. As expected, LLPs are negatively correlated with CAR in Table 1.2, 1.3 and 1.4, implying that lower regulatory capital ratios are followed by increases in bank provisions. Similarly, LLPs are negative and significantly correlated with ΔGDP in Table 1.2, 1.3 and 1.4 indicating that bank provisions are correlated with economic cycle fluctuations. Overall, with the exception of NPLs, all correlation coefficients are sufficiently low to be concerned about multicollinearity in the study.

Table 1.2. Pearson Correlation for Full Sample

	LLP	NPL	LOAN	CAR	SIZE	EBTP	ΔGDP
LLP	1.000						
NPL	0.702*** (0.000) 33.52	1.000					
LOAN	-0.143*** (0.000) -4.92	-0.224*** (0.000) -7.82	1.000				

CAR	-0.089*** (0.002) -3.06	-0.044 (0.133) -1.51	-0.251*** (0.000) -8.85	1.000			
SIZE	-0.067** (0.023) -2.28	-0.044 (0.136) -1.49	-0.083*** (0.005) -2.82	0.023 (0.433) 0.78	1.000		
EBTP	-0.0003 (0.992) -0.01	-0.025 (0.377) -0.88	0.256*** (0.000) 9.01	-0.048 (0.103) -1.63	-0.116*** (0.000)	1.000	
ΔGDP	-0.255*** (0.000) -8.96	-0.275*** (0.000) -9.75	0.246*** (0.000) 8.62	-0.066 (0.025) -2.25	0.037 (0.205) 1.27	0.114*** (0.000) 3.90	1.000

Table 1.2 provides the Pearson correlation for the full sample for the 2004 to 2013 period.
*, **, *** represent statistical significance at 10%, 5% and 1% levels. P-values are reported in parenthesis. Standard errors (t-statistics) are reported below the p-values

Table 1.3. Pearson Correlation for G-SIBs

	LLP	NPL	LOAN	CAR	SIZE	EBTP	ΔGDP
LLP	1.000						
NPL	0.568*** (0.000) 10.16	1.000					
LOAN	-0.229*** (0.000) -3.46	-0.372*** (0.000) -5.89	1.000				
CAR	-0.048 (0.477) -0.71	0.187*** (0.005) 2.81	-0.393*** (0.000) -6.31	1.000			
SIZE	-0.043 (0.521) -0.64	0.194*** (0.004) 2.92	-0.033 (0.624) -0.49	0.127* (0.061) 1.89	1.000		
EBTP	0.482*** (0.000) 8.09	0.009 (0.893) 0.13	0.262*** (0.000) 3.99	-0.335*** (0.000) -5.23	-0.288*** (0.000) -4.43	1.000	
ΔGDP	-0.404*** (0.000) -6.51	-0.245*** (0.000) -3.73	0.321*** (0.000) 4.99	-0.250*** (0.000) -3.86	0.026 (0.705) 0.38	-0.012 (0.862) -0.17	1.000

Table 1.3 provides the Pearson correlation for G-SIBs sample for the 2004 to 2013 period.
*, **, *** represent statistical significance at 10%, 5% and 1% levels. P-values are reported in parenthesis.
Standard errors (t-statistics) are reported below the p-values

Table 1.4. Pearson Correlation for Non-G-SIBs

	LLP	NPL	LOAN	CAR	SIZE	EBTP	ΔGDP
LLP	1.000						
NPL	0.704*** (0.000) 30.18	1.000					
LOAN	-0.141*** (0.000) -4.34	-0.218*** (0.000) -6.79	1.000				
CAR	-0.098*** (0.003) -3.01	-0.067** (0.040) -2.06	-0.247*** (0.000) -7.76	1.000			
SIZE	-0.047 (0.149) -1.44	-0.039 (0.223) -1.22	-0.021 (0.526) -0.63	0.076** (0.020) 2.33	1.000		
EBTP	-0.023 (0.476) -0.71	-0.032 (0.335) -0.96	0.251*** (0.000) 7.89	-0.0502 (0.125) -1.53	-0.131*** (0.000) -4.03	1.000	
ΔGDP	-0.244*** (0.000) -7.68	-0.275*** (0.000) -8.72	0.230*** (0.000) 7.21	-0.037 (0.258) -1.13	0.003 (0.939) 0.08	0.145*** (0.000) 4.48	1.000

Table 1.4 provides the Pearson correlation for the non-GSIBs sample for the 2004 to 2013 period.
*, **, *** represent statistical significance at 10%, 5% and 1% levels. P-values are reported in parenthesis. Standard errors (t-statistics) are reported below the p-values

5.1.2. SIZE as a systemic risk determinant

SIZE is considered to be a systemic risk determinant (BCBS, 2013). Table 1.5. shows that the size of G-SIBs were larger in 2004 but marginally reduced in their average and median size in 2014. This reduction in size can be explained by the post-crisis excessive regulation that created incentives for system banks to reduce their systemic risk exposure, prompting banks to reduce their size, as size is a key determinant of systemic risk. Non-G-SIBs, on the other hand, were smaller in 2004 and only marginally inceased in size in 2014. Table 1.6. show that the size of GSIBs and non-GSIBs in 2014 are less correlated (0.613) than their sizes in 2004 (0.840).

Table 1.5. Descriptive Statistics for Bank size in 2004 and 2014 (GSIB vs Non-GSIB)

	$GSIB_{Y14}$	Non-$GSIB_{Y14}$	$GSIB_{Y4}$	Non-$GSIB_{Y4}$
MEAN	19.602	18.306	19.653	17.706
MEDIAN	19.914	18.009	20.397	17.567
S.D.	1.638	1.0927	1.575	1.297

$GSIB_{Y14}$ = Year-2014 observations for G-SIBs. Non-$GSIB_{Y14}$ = Year-2014 observations for non-G-SIBs. $GSIB_{Y4}$ = Year-2004 observations for G-SIBs. Non-$GSIB_{Y4}$ = Year-2004 observations for non-G-SIBs

Table 1.6. Correlation for Bank size in 2004 and 2014 (GSIB vs Non-GSIB)

	$GSIB_{Y14}$	$Non\text{-}GSIB_{Y14}$	$GSIB_{Y4}$	$Non\text{-}GSIB_{Y4}$
$GSIB_{Y14}$	1			
$Non\text{-}GSIB_{Y14}$	0.613***	1		
$GSIB_{Y4}$	0.857*	0.805*	1	
$Non\text{-}GSIB_{Y4}$	0.602*	0.897**	0.840*	1

***,**,* denote significance at 1%, 5% and 10% levels.

5.2. Regression Results: Income Smoothing

5.2.1. Income Smoothing

Table 2 reports the result to test the income smoothing hypothesis. For the full sample, EBTP coefficient is negative and insignificant in Column 1 but is significant in Column 2 & 3 which implies that the results are inconclusive across the three estimations. We believe that the negative EBTP coefficient reported for the full sample is due to the large number of non-G-SIBs that make up the full sample compared to the number of G-SIBs, as the non-G-SIBs result report a negative EBTP coefficient. For the G-SIBs sample, EBTP coefficient is positively significant across the three estimations, implying that G-SIBs use LLPs to smooth income over the period examined. This finding supports the income smoothing hypothesis and is consistent with the findings of Leventis et al (2011) and Curcio and Hasan (2015). The observed income smoothing behaviour for G-SIBs suggest that G-SIBs use LLPs to smooth reported earnings, possibly, as a bank stability tool although the manipulation of LLPs to smooth income may reduce the reliability and informativeness of LLPs. For the non-G-SIBs sample, EBTP coefficient is positive and insignificant in Column 7 and is negatively significant in Column 8 & 9, implying that the results are not consistent across all estimations. In fact, the OLS estimation reports a significant negative sign for EBTP coefficient which implies that non-G-SIBs do not use LLPs to smooth income. Taken together, the findings support our first hypothesis which argues that G-SIBs use LLPs to smooth income to a greater extent than non-G-SIBs. The lack of evidence for income smoothing among non-G-SIBs may be due to non-G-SIBs relying on alternative accounting numbers to smooth reported earnings other than loan loss provisions (LLP).

With regard to the control variables, CAR coefficient is negatively significant for the full sample, highly significant for G-SIBs, and insignificant for non-G-SIBs. This indicates that the propensity to use LLPs to manage regulatory capital is significantly associated with G-SIBs than non-G-SIBs which is achieved by increasing (decreasing) LLPs when they have less (more) Tier 1 capital. Bonin and Kosak (2013) also find similar evidence for bank in emerging European countries. NPL coefficient is positively significant in all estimations for the full sample, G-SIBs and for non-G-SIBs, implying that banks increase LLPs when they expect higher non-performing loans. LOAN coefficient reports a negative sign but is insignificant for G-SIBs and non-G-SIBs. SIZE coefficient is negatively significant for the full sample and report inconsistent results for G-SIBs and non-G-SIBs across the three estimations. This is inconsistent with Anandarajan et al (2007) who posit a positive relationship because larger banks should keep higher provisions due to their higher levels of business activities. As expected, ∆GDP coefficient reports a negative sign for the full sample, G-SIBs and non-G-SIBs while showing mixed significance levels for ∆GDP coefficient. However, ∆GDP coefficient is negatively significant in Column 4, implying that the provisioning of G-SIBs is procyclical with economic fluctuations.

Table 2: Main Regression - Income Smoothing

LLPt-1 = lagged loan loss provisions to total asset ratio. EBTP = earnings before tax and provisions to total asset ratio. NPL = non-performing loans to gross loan ratio. LOAN = loan growth rate CAR tier 1 capital to risk weighted assets. SIZE = natural logarithm of total assets. ∆GDP = real gross domestic product growth rate. The three sample categories are estimated using the (i) Arellano and Bond (1991) GMM first difference estimator, (ii) panel OLS estimator with lagged dependent variable following Bikker and Metzemakers (2005) and (iii) the panel OLS estimator. The GMM and OLS results for EBPT coefficient are consistent across the three estimators. Standard errors are not clustered. T-statistics are reported in parenthesis. ***, ** & * represent 1%, 5% and 10% significance levels.

	Exp. Sign	(A)Full Sample			(B) European G-SIBs			(C) European Non-G-SIBs		
Variables		GMM	Lagged OLS	OLS	GMM	Lagged OLS	OLS	GMM	Lagged OLS	OLS
		Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
c			0.021* (1.70)	0.027** (2.15)		-0.018 (-1.43)	-0.019 (-1.53)		0.039** (2.42)	0.048*** (2.99)
LLPt-1	?	-0.144* (-1.67)	0.248*** (6.27)		0.133*** (5.69)	-0.016 (-0.20)		-0.089 (-0.83)	0.255*** (5.79)	
EBTP	+	-0.012 (-0.12)	-0.077*** (-3.32)	-0.068*** (-2.94)	0.394*** (10.37)	0.347*** (6.36)	0.342*** (6.47)	0.007 (0.05)	-0.089*** (-3.44)	-0.081*** (-3.10)
NPL	+	0.0005* (2.10)	0.0009*** (13.98)	0.001*** (23.73)	0.0007*** (3.59)	0.001*** (6.06)	0.001 (6.87)	0.0006* (1.85)	0.0009*** (12.51)	0.001*** (21.47)
LOAN	+/-	-0.0001** (-1.84)	-0.00001 (-0.69)	-0.00006 (-0.44)	-0.0001 (-0.88)	-0.0001 (-0.81)	-0.00001 (-0.96)	-0.0001 (-0.96)	-0.0001 (-0.81)	-0.00001 (-0.63)
CAR	-	-0.009*** (-2.57)	-0.0001* (-1.65)	-0.0001 (-1.50)	-0.0006*** (-5.21)	-0.0003*** (-2.62)	-0.0003*** (-2.66)	-0.001 (-0.86)	-0.0001 (-1.27)	-0.0001 (-1.09)
SIZE	+	-0.011** (-2.12)	-0.0001* (-1.61)	-0.001** (-2.09)	-0.001* (-1.71)	0.0009 (1.46)	0.0009 (1.57)	-0.011 (-1.10)	-0.002** (-2.35)	-0.003*** (-2.97)
∆GDP	-	-0.0007** (-1.87)	-0.0003** (-2.33)	-0.0003** (-2.23)	0.0002*** (2.97)	-0.00005 (-0.29)	-0.00003 (-0.15)	-0.001 (-1.25)	-0.0003** (-2.01)	-0.0003* (-1.89)
Bank Fixed Effects?		Yes	Yes		Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects?		Yes	Yes		Yes	Yes	Yes	Yes	Yes	Yes
Sarjan (J Statistic)		18.83	-		20.97	-	-	10.89	-	-
p-value (J Statistic)		0.42	-		0.23	-	-	0.96	-	-
AR(1)		0.000	-		0.118	-	-	0.012	-	-
AR(2)		0.105	-		0.519	-	-	0.074	-	-
Adjusted R^2		-	77.26	71.64	-	67.34	74.31	-	73.04	72.03
F-statistic		-	16.57	16.26	-	10.62	11.2	-	16.54	16.14
D-W statistic		-	1.97	1.59	-	2.02	1.99	-	1.98	1.60
Observations		941	1118	1149	179	211	219	762	907	930

5.2.2. Pre- and Post-Financial Crisis

Based on the full sample, we test for differential income smoothing behaviour among G-SIBs relative to non-G-SIBs. We introduce 'GSIB' dummy variable that takes the value of one if the bank is a G-SIB and zero otherwise. This allows us to compare G-SIBs and non-G-SIBs based on the full sample. We use OLS to estimate the result because of the presence of the time-invariant dummy variable. G-SIB*EBTP coefficient is positively significant indicating that G-SIBs use LLPs to smooth income to a greater extent than non-G-SIBs and support our hypothesis that G-SIBs smooth income to a greater extent than non-G-SIBs. Next, we introduce 'CRISIS' dummy that takes the value of one for the post-crisis period (2009, 2010, 2011, 2012 and 2013) and zero for the pre-crisis period (2004, 2005, 2006 and 2007). We interact 'CRISIS' with GSIB*EBTP variable. CRISIS*GSIB*EBTP coefficient is positively significant at 5%, which indicates that G-SIBs use LLP to smooth income during the post-crisis period compared to non-G-SIBs.

Further, we divided the G-SIB and non-G-SIB sample into the pre-crisis, during-crisis and post-crisis subsamples. The results in Table 3 show that income smoothing is more pronounced among non-G-SIBs in the pre-crisis period but not during the crisis nor in the post-crisis period. This implies that non-G-SIBs did not use LLPs to smooth income in the pre-crisis which was associated with economic boom. This finding do not support the finding of Liu and Ryan (2006) who find that banks use LLPs to smooth income during economic booms. On the other hand, income smoothing is more pronounced among G-SIBs in the post-crisis period. Moreover, we did not find evidence for income smoothing during the crisis period for both G-SIBs and non-G-SIBs which contradict the findings of El Sood (2012) who find that US banks use LLPs to smooth income during the crisis period.

Table 3: Financial crisis: G-SIBs and non-G-SIBs

Regressions are estimated using OLS regression because the small sample period and insufficient number of instruments breakdown the GMM estimator. In Column (1) & (2) GSIB is a dummy that takes the value 1 if the bank is a G-SIB and zero otherwise. We follow Bikker and Metzemakers (2005) and include lagged dependent variable into the model. EBTP = earnings before tax and provisions to total asset ratio. NPL = non-performing loans to gross loan ratio. LOAN = loan growth rate CAR tier 1 capital to risk weighted assets. SIZE = natural logarithm of total assets. ΔGDP = real gross domestic product growth rate. GSIB = dummy variable that equal one if the bank is a G-SIB and zero for non-G-SIBs. CRISIS = dummy variable that equal one for the post-crisis period and zero for the pre-crisis period.

	Full Sample			European G-SIB Subsample (Fixed Effect OLS)			European non-G-SIB Subsample Non-G-SIBs (Fixed Effect OLS)		
	(Interaction Regression)			Pre-Crisis (2004-2006)	During Crisis (2007-2009)	Post-Crisis (2010-2013)	Pre-Crisis (2004-2006)	During Crisis (2007-2009)	Post-Crisis (2010-2013)
	(1)	(2a)	(2b)	(3)	(4)	(5)	(6)	(7)	(8)
	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)
c				0.055*** (2.66)	0.047 (0.58)	0.023 (0.76)	0.002 (0.19)	0.023 (0.56)	-0.004 (-0.13)
LLPt-1	0.709*** (6.79)	0.716*** (7.28)	0.734*** (22.83)	-0.234 (-1.15)	1.134** (2.20)	0.159** (2.17)	0.203*** (2.69)	0.219* (1.92)	-0.191 (-3.54)
EBTP	-0.043 (-0.82)	-0.041 (-0.88)	-0.059*** (-3.03)	0.049 (1.15)	-0.204** (-2.08)	0.297*** (4.35)	0.042* (1.77)	0.061 (0.95)	-0.107*** (-3.62)
NPL	0.0004*** (3.77)	0.0004*** (2.88)	0.0005*** (10.73)	0.00002 (0.96)	0.003*** (4.43)	0.0009*** (3.15)	0.0003*** (3.89)	0.001*** (9.65)	0.009*** (8.64)
LOAN	0.000004 (0.23)	-0.00004 (-0.27)	-0.0001 (-0.41)	-0.00001 (-1.17)	-0.00002 (-0.01)	0.00002 (1.29)	0.000003 (0.85)	-0.0001 (-1.06)	-0.00001 (-0.49)
CAR	-0.0001*** (-2.67)	-0.00008 (-1.58)	-0.0001 (-1.50)	-0.00004 (-0.31)	-0.001*** (-2.27)	-0.0004** (-2.52)	-0.00001 (-0.23)	-0.0001 (-0.04)	-0.0002* (-1.68)
SIZE	0.00009 (1.50)	0.00008** (2.03)	-0.0002 (-1.23)	-0.003*** (-2.66)	-0.005 (-0.57)	-0.001 (-0.75)	-0.000004 (-0.23)	-0.003 (-0.59)	0.0005 (0.29)
ΔGDP	-0.0004*** (-4.09)	-0.0005*** (-5.49)	-0.0001 (-1.13)	0.0002 (1.09)	0.0005 (0.17)	0.00002 (0.07)	-0.00003 (-0.37)	-0.00004 (-0.16)	-0.0004 (-1.39)
GSIB	-0.002** (-2.13)	-0.001** (-2.26)	-0.0006 (-0.95)						
GSIB*EBTP	0.177* (1.70)								
CRISIS		-0.0002*** (-3.60)							
GSIB*CRISIS*EBTP		0.130** (2.05)							
LISTED			-0.0005 (-1.26)						
LISTED*GSIB*EBTP			0.121* (1.80)						
Bank Fixed Effect	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Adjusted R^2	65.51	65.59	65.92	88.97	91.35	77.24	94.32	80.82	84.27
Observations	1125	1125	1125	65	58	117	242	259	538

5.2.3. G-SIBs: Transient Income Smoothing

The results are reported in Table 4. With respect of the size of earnings (or earnings distribution), POS*EBTP is negatively significant, HIGH*EBTP report a negative sign but is insignificant while NEG*EBTP coefficient is positively significant. The coefficient signs for POS*EBTP and HIGH*EBTP coefficients indicate that G-SIBs do not use provisions to smooth positive (or substantial) earnings; put differently, G-SIBs do not use provisions to smooth income when they are more profitable; and this result does not support the second hypothesis. In contrast, Balboa et al (2013) observe that US banks use provisions to smooth positive (or substantial earnings).

On the other hand, NEG*EBTP coefficient is positively significant in Column 3 indicating that G-SIBs use LLPs to smooth earnings when they expect losses i.e., negative earnings, possibly to minimise losses. This result supports the second hypothesis which argues that income smoothing by G-SIBs depends on the size of earnings (in this case, losses or negative earnings). This result is consistent with El Sood (2012) who finds that US banks smooth income to minimise losses during financial crisis period. With respect to regulatory capital, WC*EBTP coefficient is positive but insignificant. REC*EBTP coefficient is positively significant indicating that G-SIBs use LLPs to smooth income during economic downturns/recessions and is consistent with El Sood (2012) and supports the third hypothesis. This finding is interesting because it expounds the concern of bank regulators who require G-SIBs to keep sufficient provisions and capital buffers in anticipation of recessionary periods. BOOM*EBTP coefficient is negatively significant indicating that G-SIBs do not use LLPs to smooth income during economic booms. BIG*EBTP coefficient is insignificant. NPLD*EBTP coefficient is positively significant, indicating that G-SIBs use LLPs to smooth income when they have significant non-performing loans possibly to reduce the negative signalling consequence of large loan losses on bank profitability.

Table 4: European G-SIBs: Transient Income Smoothing (GMM)

LLPt-1 = lagged loan loss provisions to total asset ratio. EBTP = earnings before tax and provisions to total asset ratio. NPL = non-performing loans to gross loan ratio. LOAN = loan growth rate CAR tier 1 capital to risk weighted assets. SIZE = natural logarithm of total assets. ΔGDP = real gross domestic product growth rate. POS&HIGH = non-negative and above-the-median EBTP reflecting periods when G-SIBs are more profitable. REC = negative ΔGDP reflecting periods of economic downturn. BOOM = above-the-median ΔGDP reflecting periods of economic prosperity. WC = above 8% CAR reflecting periods when G-SIBs have sufficient regulatory capital. NPLD = double-digit NPLs reflecting periods when G-SIBs have deteriorating asset quality. BIG = above-the-median SIZE reflecting periods when G-SIBs are bigger/larger. The sample is estimated using the Arellano and Bond (1991) GMM first difference estimator. Standard errors are not clustered. T-statistics are reported in parenthesis. ***, ** & * represent 1%, 5% and 10% significance levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)
LLPt-1	0.155*** (5.39)	0.145*** (6.09)	0.155*** (5.39)	0.137*** (5.75)	0.169*** (6.99)	0.179*** (5.41)	0.155* (1.80)	0.205*** (7.68)	0.293*** (4.91)
EBTP	1.284*** (5.98)	0.777*** (5.19)	1.284*** (5.98)	0.355*** (5.43)	0.183*** (2.89)	0.389*** (12.12)	0.271*** (3.60)	0.503*** (10.01)	0.475*** (8.50)
NPL	0.0006*** (3.02)	0.001*** (3.31)	0.0006*** (3.02)	0.0004* (1.82)	0.0005** (2.53)	0.0004* (1.90)	0.001*** (4.78)	0.0005 (1.48)	
NPLt-1									0.001*** (5.14)
LOAN	-0.00004** (-2.57)	0.00003 (1.04)	-0.00004** (-2.57)	-0.00004 (-1.92)	-0.00002 (-0.79)	-0.00006** (-2.39)	0.00004 (1.07)	-0.00001 (-0.67)	
LOANt-1									-0.00001 (-0.55)
CAR	-0.0006*** (-3.57)	0.0001 (0.39)	-0.0006*** (-3.57)	-0.0006** (-2.45)	-0.0005*** (-3.54)	-0.0006*** (-4.11)	-0.0004** (-2.25)	-0.0003 (-1.54)	
CARt-1									-0.0005*** (-3.35)
SIZE	0.003** (2.14)	0.007*** (3.01)	0.003** (2.14)	-0.002 (-1.09)	-0.002* (-1.80)	-0.001 (-1.19)	-0.006*** (-2.86)	-0.004 (-1.24)	
SIZEt-1									0.004** (2.56)
ΔGDP	0.0004*** (3.06)	-0.0005** (2.10)	0.0004*** (3.06)	0.0004* (1.83)	0.003*** (5.64)	0.0004** (2.48)	0.0001 (1.16)	0.0003 (0.62)	-0.0002 (-1.50)
POS	-0.009*** (-8.68)								
POS*EBTP	-0.755*** (-3.65)								
HIGH		-0.005** (-2.58)							
HIGH*EBTP		-0.201 (-1.22)							
NEG			0.009*** (8.68)						
NEG*EBTP			0.755*** (3.65)						
WC				-0.002 (-1.05)					
WC*EBTP				0.116 (0.95)					
REC					0.003** (2.13)				
REC*EBTP					0.186*** (4.28)				
BIG						-0.004*** (-2.82)			
BIG*EBTP						0.109 (1.03)			
NPLD							-0.013*** (-6.32)		

NPLD*EBTP							0.509*** (8.17)		
BOOM								0.003*** (2.79)	
BOOM*EBTP								-0.195*** (-5.18)	
J-statistic	17.38	16.52	17.38	20.19	19.55	17.92	17.02	17.57	15.99
P (J-statistic)	0.29	0.35	0.29	0.16	0.19	0.27	0.32	0.286	0.453
AR(1)	0.066	0.084	0.66	0.074	0.043	0.066	0.121	0.078	
AR(2)	0.916	0.304	0.916	0.743	0.879	0.967	0.759	0.555	
Observations	179	179	179	179	179	179	179	179	158

5.2.4. Non-G-SIBs: Transient Income Smoothing

The results are reported in Table 5. For non-G-SIBs, POS*EBTP and HIGH*EBTP coefficients are insignificant respectively indicating that non-G-SIBs do not use LLPs to smooth income when they are more profitable. NEG*EBTP coefficient is positive but insignificant indicating that non-G-SIBs do not use LLPs to smooth income when they expect losses. REC*EBTP coefficient is insignificant indicating that income smoothing is not pronounced among non-G-SIBs during recessionary periods. WC*EBTP coefficient is also positive but insignificant while NPLD*EBTP, BOOM*EBTP and BIG*SIZE coefficients do not report significant signs.

Table 5: European non-G-SIBs: Transient Income Smoothing (GMM)

LLPt-1 = lagged loan loss provisions to total asset ratio. EBTP = earnings before tax and provisions to total asset ratio. NPL = non-performing loans to gross loan ratio. LOAN = loan growth rate CAR tier 1 capital to risk weighted assets. SIZE = natural logarithm of total assets. ΔGDP = real gross domestic product growth rate. POS&HIGH = non-negative and above-the-median EBTP reflecting periods when G-SIBs are more profitable. REC = negative ΔGDP reflecting periods of economic downturn. BOOM = above-the-median ΔGDP reflecting periods of economic prosperity. WC = above 8% CAR reflecting periods when non-G-SIBs have sufficient regulatory capital. NPLD = double-digit NPLs reflecting periods when non-G-SIBs have deteriorating asset quality. BIG = above-the-median SIZE reflecting periods when non-G-SIBs are bigger/larger. The sample is estimated using the Arellano and Bond (1991) GMM first difference estimator. Standard errors are not clustered. T-statistics are reported in parenthesis. ***, ** & * represent 1%, 5% and 10% significance levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)
LLPt-1	-0.056 (-0.43)	-0.071 (-0.58)	-0.056 (-0.43)	-0.046 (-0.29)	-0.004 (-0.04)	-0.066 (-0.59)	-0.012 (-0.07)	-0.056 (-0.48)	-0.378 (-2.04)
EBTP	-0.058 (-0.31)	-0.060 (-0.47)	-0.058 (-0.31)	-0.220 (-0.80)	-0.019 (-0.07)	0.116 (0.64)	-0.409 (-0.72)	-0.022 (-0.15)	-0.119 (-1.08)
NPL	0.0006** (1.84)	0.0006* (1.96)	0.0006* (1.84)	0.0005 (1.32)	0.0005 (1.34)	0.0006 (1.60)	0.002*** (2.69)	0.0004 (1.09)	
NPLt-1									0.0005 (2.75)
LOAN	-0.0001 (-0.96)	-0.0001 (-1.31)	-0.0001 (-0.96)	-0.0001 (-0.44)	-0.00007 (-0.57)	-0.0001 (-0.81)	-0.0002 (-1.08)	-0.0001 (-0.63)	
LOANt-1									-0.0002 (-2.44)
CAR	-0.0005 (-0.77)	-0.0008 (-1.28)	-0.0005 (-0.77)	-0.0003 (-0.46)	-0.0005 (-0.73)	-0.0005 (-0.77)	-0.002 (-1.14)	-0.0005 (-0.65)	
CARt-1									-0.001 (-2.76)
SIZE	-0.008 (-0.73)	-0.010 (-1.23)	-0.008 (-0.73)	-0.009 (-0.90)	-0.013 (-1.16)	-0.008 (-0.71)	-0.041*** (-2.60)	-0.016 (-1.20)	
SIZEt-1									0.0008 (0.15)
ΔGDP	-0.0006 (-0.78)	-0.001 (-1.40)	-0.0006 (-0.78)	-0.0006 (-0.83)	-0.0005 (-0.70)	-0.0008 (-1.19)	-0.002 (-1.31)	-0.0006 (-0.79)	-0.0008 (-1.61)
POS	0.005 (0.61)								
POS*EBTP	-0.009 (-0.04)								
HIGH		0.003 (0.50)							
HIGH*EBTP		0.038 (0.13)							
NEG			-0.005 (-0.61)						
NEG*EBTP			0.009 (0.04)						
WC				-0.007 (-1.18)					

WC*EBTP				0.269 (0.82)					
REC					0.006 (1.41)				
REC*EBTP					0.028 (0.12)				
BIG						-0.001 (-0.12)			
BIG*SIZE						-0.189 (-0.67)			
NPLD							-0.021 (-1.61)		
NPLD*EBTP							0.348 (0.58)		
BOOM								0.003 (0.92)	
BOOM*EBTP								-0.288 (-1.13)	
J-Statistics	10.63	10.37	10.63	9.33	8.02	9.97	6.67	8.89	20.75
Pvalue (J-statistic)	0.94	0.94	0.94	0.96	0.98	0.95	0.99	0.975	0.474
Instrument rank	35	35	35	35	35	35	35	35	35
AR(1)	0.036	0.001	0.036	0.016	0.004	0.009	0.017	0.015	
AR(2)	0.128	0.071	0.128	0.218	0.218	0.067	0.174	0.125	
Observations	762	762	762	762	762	762	762	762	651

5.3. Further Issues and Robustness Checks

5.3.1 Transient Incentives: Interaction

We perform further test in Table 6, we check whether G-SIBs and non-G-SIBs use LLPs to smooth income when they have substantial non-performing loans during recessionary periods. To do this, we interact 'NPLD' variable with 'REC' variable and we draw inference from the NPLD*REC*EBTP coefficient. NPLD*REC*EBTP coefficient is insignificant for G-SIBs and non-G-SIBs. We also check whether G-SIBs and non-G-SIBs use LLPs to smooth income when they are large and during recessionary periods. To do this, we interact 'BIG' variable with 'REC' variable and we draw inference from the BIG*REC*EBTP coefficient. BIG*REC*EBTP coefficient is positively significant for G-SIBs but not for non-G-SIBs implying that larger G-SIBs use LLPs to smooth income during recessionary periods.

Finally, reporting excessive profits can have signalling consequences (Leventis et al, 2012) and Watts and Zimmerman (1986) argue that very large banks have incentives to lower excessive profit if reporting excessive profit could have unintended signalling consequences to regulators and other commentators. White et al. (2003) stress that the way the general public, politicians and regulators view extremely high earnings of a firm differ from the way shareholders perceive high earnings, particularly, if there is a reason to believe that a firm or group of firms are taking advantage of the public by making obscene profits. Watts and Zimmerman (1986) further argue that, because extremely high earnings could attract political criticism and regulatory scrutiny and such scrutiny is costly to firms, firm managers have incentive to use accounting procedures that reduce high earnings in the current period. Therefore, G-SIBs can smooth income to lower excessive profit if excessive profit could have unintended signalling consequences to regulators and the general public. A counter argument that is G-SIBs have less incentive to smooth income because well capitalized and profitable banks are not a problem for systemic stability. To test these hypotheses, we check whether G-SIBs and non-G-SIBs use LLPs to smooth income when they are more profitable and exceed minimum capital ratios. WC*HIGH*EBTP and WC*POS*EBTP coefficients are positively significant for G-SIBs but not for non-G-SIBs implying that G-SIBs use LLPs to smooth income when they are profitable and exceed minimum regulatory capital ratios, and the findings supports the arguments of Watts and Zimmerman (1986) and White et al. (2003) as indicated above.

Table 6: Additional Analysis

All regression are based on GMM regression. All variables remain as previously defined in Table 4&5. Standard errors are not clustered. T-statistics are reported in parenthesis. ***, ** & * represent 1%, 5% and 10% significance levels.

	G-SIBs					Non-G-SIBs				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)
LLPt-1	0.309*** (4.14)	0.225*** (5.89)	0.088*** (2.87)	0.100** (2.59)	0.135*** (4.67)	0.124 (0.22)	-0.044 (-0.30)	-0.262 (-1.55)	-0.145 (-0.96)	-0.029 (-0.19)
EBTP	0.279*** (3.31)	0.422*** (7.51)	0.497*** (7.16)	0.464*** (12.39)	0.535*** (8.73)	0.215 (0.41)	-0.191 (-1.14)	-0.017 (-0.11)	0.006 (0.03)	-0.109 (-0.50)
NPL	0.001*** (3.16)	0.0006* (1.91)	0.002*** (3.28)	0.0006** (2.02)	0.0006** (2.46)	0.0008 (1.59)	0.0006 (1.89)	0.0008** (2.50)	0.0007** (2.36)	0.0005** (2.09)
LOAN	0.00001 (0.41)	-0.00003 (-1.42)	0.0001 (1.56)	-0.00002 (-0.64)	-0.00004 (-2.29)	-0.0002 (-0.69)	-0.0001 (-0.51)	-0.00003 (-0.21)	-0.00002 (-0.17)	-0.0001 (-0.48)
CAR	-0.0001 (-0.24)	-0.0007*** (-2.83)	0.0002 (0.69)	-0.0004** (-2.35)	-0.0005*** (-3.24)	-0.0002 (-0.31)	-0.0002 (-0.31)	-0.001* (-1.31)	-0.0008 (-1.32)	-0.0004 (-0.66)
SIZE	-0.005*** (-2.82)	-0.002 (-1.03)	0.005** (2.44)	0.003 (1.37)	0.003 (1.56)	-0.002 (-0.25)	-0.0009 (-0.13)	-0.0001 (-0.01)	-0.0005 (-0.06)	-0.0001 (-0.02)
ΔGDP	0.00001 (0.08)	0.0002 (1.58)	-0.0006** (-2.25)	0.0003** (2.49)	0.0004** (2.34)	-0.001 (-0.84)	-0.0005 (-0.46)	-0.0009 (-1.34)	-0.0008 (-0.97)	-0.0006 (-0.74)
NPLD	-0.006*** (-3.51)					-0.002 (-0.20)				
REC	0.0001 (0.05)	0.0001 (0.06)			0.0004 (0.34)	-0.001 (-0.13)	0.002 (0.37)			0.003** (0.68)
NPLD*REC*EBTP	-0.149 (-0.58)					-0.304 (-0.61)				
BIG		-0.003*** (-3.35)					-0.003 (-0.25)			
REC*BIG*EBTP		0.208* (1.82)					-0.045 (-0.15)			
HIGH			-0.009*** (-5.89)					0.008 (1.09)		
WC			-0.006*** (-4.65)	-0.004*** (-3.13)				-0.008 (-1.23)	-0.006 (-1.06)	
WC*HIGH*EBTP			0.392*** (4.65)					-0.390 (-0.83)		
POS				-0.011*** (-8.48)					0.002 (0.16)	
WC*POS*EBTP				0.269*** (2.75)					-0.231 (-0.70)	
NEG					0.009*** (6.82)					-0.0009 (-0.10)
REC*NEG*EBTP					0.594** (2.36)					0.082 (0.36)
J-Statistic	17.78	11.43	13.44	13.11	16.67	7.56	9.89	9.05	7.69	10.34
P-value (J-statistic)	0.216	0.652	0.492	0.517	0.274	0.984	0.935	0.958	0.983	0.920
AR(1)	0.117	0.108	0.0001	0.040	0.065	0.065	0.005	0.003	0.028	0.006
AR(2)	0.401	0.939	0.033	0.139	0.835	0.125	0.269	0.171	0.133	0.189
Instrument rank	31	31	31	31	31	35	35	35	35	35
Observation	179	179	179	179	179	761	761	762	762	761

5.3.2 Forward looking Bank Provisioning

We also address the issue of forward looking provisioning. The Financial Stability Board (FSB) raised concern that bank provisioning should be forward-looking in anticipation of economic downturns (FSF, 2009). However, since the FSB did not state the practical way that banks should follow to engage in forward-looking provisioning, bank managers continue to have significant discretion on forward-looking bank provisioning which is argued to create opportunities for banks to use LLPs to smooth reported earnings (Bushman and Williams 2012). We test this clam for G-SIBs and non-G-SIBs, to check whether G-SIBs and non-G-SIBs also exploit their discretion in forward-looking provisioning to smooth income. We modify Bushman and Williams (2012)'s model and estimate LLPs as a function of lagged (or beginning) values of the explanatory variables except EBTP and ΔGDP. We take the beginning values of the explanatory variables to ensure that bank provisions only pick up earnings manipulation and changing economic conditions without reference to current information about bank loan portfolio (i.e., the bank-level explanatory variables). This allows us to detect whether managers of G-SIBs and non-G-SIBs exploit forward-looking provisioning to smooth reported earnings.

$$LLPit = \beta 1 + \beta 2EBTPit + \beta 3LLPit - 1 + \beta 4NPLit - 1 + \beta 5LOANit - 1 + \beta 6CARit - 1 + \beta 7\Delta GDPjt + \beta 8SIZEit - 1 + eit. \qquad Eq\,(4)$$

EBTP coefficient is positively significant in Column 9 of Table 4 indicating that LLPs are used to smooth income and implies that managers of G-SIBs exploit their discretion in forward-looking provisioning to smooth income while the EBTP coefficient for non-G-SIBs do not report significant evidence for income smoothing via LLPs in Column 9 of Table 5. The implication is that the proposed attempts by accounting standard-setters to replace the current loan loss accounting rules with a more forward-looking provisioning rule in 2018 intended to reduce the procyclicality of bank provisions is likely to lead to unintended consequences that would rather allow G-SIBs to exploit forward-looking discretion to manipulate/smooth earnings, reducing the transparency of bank provisions and reported earnings to outsiders including bank supervisors. Also, the ΔGDP coefficient for G-SIBs and non-G-SIBs are both negative but insignificant implying that forward-looking provisioning can minimise the procyclical behaviour of bank provisions.

5.3.3. Limitation of the Study

Our analyses in this paper focuses on the difference between the accounting behaviour of GSIBs and non-GSIBs with respect to loan loss provisions (not on systemic risk) to observe whether their loan loss provisions behaviour align with the financial stability objectives of bank supervisors. Although we discuss systemic risk at a conceptual level, we are aware that our study have implications for systemic risk which would favour adopting the ‘Marginal Expected Shortfall’ methodology for modelling systemic risk to see the income smoothing effect for systemic and non-systemic banks, and this methodology only works for listed banks which would substantially reduce our sample. Moreover, there is some scepticism about the ability of accounting numbers to sufficiently capture systemic risk since our analysis is based on accounting numbers, and this is another limitation of the study. Also, another option would be to use a placebo specification which requires using a different list of systemic and non-systemic banks if such list is available; therefore our narrow focus on the FSB-BCBS list is another limitation of our study.

6. Conclusion

This study examined whether the way GSIBs use accounting numbers to smooth income differ compared to non-G-SIBs and the incentives to do so. We focused on loan loss provisions – a crucial accounting number that has gained the attention of standard setters and bank supervisors. We observed that income smoothing is pronounced among G-SIBs in the post-crisis period and pronounced among non-G-SIBs in the pre-crisis period. We also find that G-SIBs exhibit greater income smoothing via LLP during recessionary periods and when they have double-digit non-performing loans. However, the trend is also observed during the periods of higher profitability, and when they meet/exceed minimum regulatory capital ratios.

The findings are useful to accounting standard setters in their evaluation of the role of reported accounting numbers for financial system stability, given the current regulatory environment in Europe which focuses on systemic banks. The implication for banking supervision is that G-SIBs possibly use LLPs to smooth income to show or create the impression that they align their behaviour with financial system stability objectives required by bank supervisors. From an accounting standard setting standpoint, the findings that G-SIBs use LLPs to smooth income to a greater extent than non-G-SIBs may be of concern to standard setters because such practices lower the reliability and informativeness of their LLP estimates. Therefore, our suggestions for regulatory/supervisory reform would be to either set up disclosure rules that improve existing disclosure rules for all bank or to impose stricter disclosure rules for G-SIBs compared to non-G-SIBs in order to improve the reliability of provisions estimates in the determination of the loan portfolio quality of G-SIBs to help bondholders and shareholders assess the credit risk of banks including G-SIBs and non-G-SIBs. Finally, the question whether G-SIBs prefer to use a single financial number or a combination of techniques to smooth income is also interesting and is a fruitful direction for future research.

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References

Acharya, V., and T. Yorulmazer (2007). Too Many To Fail - An Analysis of Time-Inconsistency in Bank Closure Policies. Journal of Financial Intermediation 16, 1–31.

Acharya, V. V. (2009). A Theory of Systemic Risk and Design of Prudential Bank Regulation. Journal of Financial Stability 5(3), 224–255.

Ahmed, A.S., C. Takeda, and S. Thomas. (1999). Bank loan loss provisions: A Reexamination of Capital Management, Earnings Management and Signaling Effects. Journal of Accounting and Economics 28, 1–25.

Alchian, A. A., and R. A. Kessel. (1962). Competition, Monopoly and the Pursuit of Money. Aspects of Labor Economics 14, 157–183.

Allen, F., and D. Gale. (2000). Financial Contagion. Journal of Political Economy, 108, 1–33.

Anandarajan, A., I. Hasan, and A. Lozano-Vivas. (2003). The Role of Loan Loss Provisions in Earnings Management, Capital Management, and Signaling: The Spanish experience. Advances in International Accounting, 16, 45–65.

Andreou, P. C., Cooper, I. A., Louca, C., & Philip, D. (2017). Bank Loan Loss Accounting Treatments, Credit Cycles and Crash Risk. British Accounting Review, Forthcoming.

Arellano, M., and S. Bond. (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. The Review of Economic Studies, 58(2), 277–297.

Balboa, M., G. López-Espinosa, and A. Rubia. (2013). Nonlinear Dynamics in Discretionary Accruals: An Analysis of Bank Loan Loss Provisions. Journal of Banking and Finance, 37(12), 5186–5207.

Barton, J. and Simko. P. (2002). The balance sheet as an earnings management constraint. Accounting Review, 77, 1-27.

BCBS. (2013). Global Systemically Important Banks: Updated Assessment Methodology and the Higher Loss Absorbency Requirement. Technical Document.

BCBS. (2014). The G-SIB Assessment Methodology: Score Calculation. Technical Document.

Beaver, W., and E. Engel. (1996). Discretionary Behaviour with Respect to Allowance for Loan Losses and the Behaviour of Security Prices. Journal of Accounting and Economics, 22, 177–206.

Bhattacharya, U., Daouk, H., & Welker, M. (2003). The world price of earnings opacity. The Accounting Review, 78(3), 641-678.

Bikker, J. A., and P. Metzemakers. (2005). Bank Provisioning Behaviour and Procyclicality. Journal of International Financial Markets, Institutions and Money, 15, 29–51.

Black, L., Correa, R., Huang, X., & Zhou, H. (2016). The systemic risk of European banks during the financial and sovereign debt crises. Journal of Banking & Finance, 63, 107-125.

Bonin, J., and M. Kosak. (2013). Loan Loss Provisioning in Emerging Europe: Precautionary or Pro-Cyclical? Working Paper, No. 10. Wesleyan University, Department of Economics.

Bouvatier, V., L. Lepetit, and F. (Strobel). 2014. Bank Income Smoothing, Ownership Concentration and the Regulatory Environment. Journal of Banking and Finance, 41, 253–270.

Brunnermeier, M. K., A. Crockett, C. A. Goodhart, A. Persaud, and H. S. Shin. (2009). The Fundamental Principles of Financial Regulation Vol. 11. London: Centre for Economic Policy Research.

Burgstahler, D. Dichev, I. (1997). Earnings management to avoid earnings decreases and losses. Journal of Accounting and Economics, 24, 99–126.

Bushman, R. M., and C. D. Williams. (2012). Accounting Discretion, Loan Loss Provisioning, and Discipline of Banks' Risk-taking. Journal of Accounting and Economics, 54(1), 1–18.

Bushman, R.M. and Williams, C.D. (2015). Delayed expected loss recognition and the risk profile of banks. Journal of Accounting Research, 53(3), 511-553.

Ching, K. M., Firth, M., & Rui, O. M. (2002). Earnings management, corporate governance and the market performance of seasoned equity offerings. Unpublished working paper, Department of Accountancy, Hong Kong Polytechnique University, Hong Kong.

Curcio, D., and I. Hasan. (2015). Earnings and Capital Management and Signaling: the Use of Loan Loss Provisions by European banks. The European Journal of Finance, 21(1), 26–50.

Curcio, D., De Simone, A., and Gallo, A. (2017). Financial crisis and international supervision: New evidence on the discretionary use of loan loss provisions at Euro Area commercial banks. The British Accounting Review, 49(2), 181-193.

Dell'Ariccia, G., E. Detragiache, and R. Rajan. (2008). The Real Effect of Banking Crises. Journal of Financial Intermediation, 17(1), 89–112.

DeGeorge, F. Patel, J. and Zeckhauser, R. (1999). Earnings management to exceed thresholds. Journal of Business, 72, 1-33.

Drehmann, M., and Tarashev, N. (2013). Measuring the systemic importance of interconnected banks. Journal of Financial Intermediation, 22(4), 586-607.

El Sood, H. A. (2012). Loan Loss Provisions and Income Smoothing in US Banks Pre and Post the Financial Crisis. International Review of Financial Analysis, 25, 64–72.

Financial Stability Forum. (2009). Report of the Financial Stability Forum on Addressing Procyclicality in the Financial System." April 2. /http://www.financialstabilityboard.org/publications/r_0904a.pdfS.

Flannery, M. J., S. H. Kwan, and M. Nimalendran. (2013). The 2007–2009 Financial Crisis and Bank Opaqueness. Journal of Financial Intermediation, 22(1), 55–84.

Fonseca, A. R., and F. González. (2008). Cross-country Determinants of Bank Income Smoothing by Managing Loan Loss Provisions. Journal of Banking & Finance, 32(2), 217–228.

FSB (2011). Policy Measures to Address Systemically Important Financial Institutions. Available at: http://www.fsb.org/2011/11/r_111104bb/ accessed on 29th November, 2017

Freixas, X., B. M. Parigi, and J. C. Rochet. (2000). Systemic Risk, Interbank Relations, and Liquidity Provision by the Central Bank. Journal of Money, Credit and Banking, 611–638.

Galati, G., and R. Moessner. (2013). Macroprudential Policy – A Literature Review. Journal of Economic Surveys, 27(5), 846–878.

Gaston, E., and Song, I.N (2014). Supervisory Roles in Loan Loss Provisioning in Countries Implementing IFRS. International Monetary Fund, Working Paper, 14/170, September.

Goodhart, C. (2015). Linkages between macro-prudential and micro-prudential supervision. Butterworths Journal of International Banking and Financial Law, 30(10), 607-609.

Gorton, G., A. Metrick, A. Shleifer, and D. K. Tarullo. (2010). Regulating the Shadow Banking System [with comments and discussion]. Brookings Papers on Economic Activity, 261–312.

Kanagaretnam, K., G. J. Lobo, and R. Mathieu. (2003). Managerial Incentives for Income Smoothing through Bank Loan Loss Provisions. Review of Quantitative Finance and Accounting, 20(1), 63–80.

Kanagaretnam, K., Lobo, G. J., & Yang, D. H. (2005). Determinants of signaling by banks through loan loss provisions. Journal of Business Research, 58(3), 312-320.

Kim, Y., C. Liu, and S G. Rhee. (2003). The Effect of Firm Size on Earnings Management. Journal of Management Research, 4, 81-88.

Laeven, C., and G. Majnoni. (2003). Loan Loss Provisioning and Economic Slowdowns: Too Much, Too Late? Journal of Financial Intermediation, 12, 178–197.

Kanagaretnam, K., Lobo, G. J., & Yang, D. H. (2005). Determinants of signaling by banks through loan loss provisions. Journal of Business Research, 58(3), 312-320.

Leventis, S., P. Dimitropoulos, and A. Anandarajan. (2011). Loan loss provisions, Earnings Management and Capital Management under IFRS: The Case of EU Commercial Banks. Journal of Financial Services Research, 40(1), 103–122.

Leventis, S., Dimitropoulos, P. E., & Anandarajan, A. (2012). Signalling by banks using loan loss provisions: the case of the European Union. Journal of Economic Studies, 39(5), 604-618.

Leventis, S. and Dimitropoulos, P. (2012). The role of corporate governance in earnings management: Experience from US banks. Journal of Applied Accounting Research, 13(2), 161-177.

Liu, C. C., and S. G. Ryan. (2006). Income smoothing over the Business Cycle: Changes in Banks' Coordinated Management of Provisions for Loan Losses and Loan Charge-offs from the Pre-1990 Bust to the 1990s Boom. The Accounting Review, 81(2), 421–441.

Lobo, G. J., and D. H. Yang. (2001). Bank Managers' Heterogeneous Decisions on Discretionary Loan Loss Provisions. Review of Quantitative Finance and Accounting, 16(3), 223–250.

López-Espinosa, G., A, Moreno, A. Rubia, and L. Valderrama. (2012). Short-term Wholesale Funding and Systemic Risk: A Global CoVaR Approach. Journal of Banking and Finance, 36(12), 3150–3162.

Ma, M.L.Z. and Song, V. (2016). Discretionary loan loss provisions and systemic risk in the banking industry. Accounting Perspectives, 15(2), 89-130

Manganaris, P., Beccalli, E. and Dimitropoulos P. (2017). Bank transparency and the crisis. The British Accounting Review, 49, 121-137.

Markose, S. (2012). Systemic risk from global financial derivatives: A network analysis of contagion and its mitigation with super-spreader tax (No. 12-282). International Monetary Fund.

Markose, S., Giansante, S., & Shaghaghi, A. R. (2012). 'Too interconnected to fail'financial network of US CDS market: Topological fragility and systemic risk. Journal of Economic Behavior & Organization, 83(3), 627-646.

Marton, J., and Runesson, E. (2017). The predictive ability of loan loss provisions in banks–Effects of accounting standards, enforcement and incentives. The British Accounting Review, 49(2), 162-180.

Mesnard, B, Margerit, A, Magnus, M, Katopodi, C. (2017). Global Systemically Important Banks in Europe: Briefing. Economic Governance Support Unit. European Parliament. Available at: http://www.europarl.europa.eu/RegData/etudes/BRIE/2016/574406/IPOL_BRI(2016)574406_EN.pdf Accessed on 11 November, 2017.

Nelson, M. W., J. A. Elliott, and R. L. Tarpley. (2002). Evidence from Auditors about Managers' and Auditors' Earnings Management Decisions. The Accounting Review, 77(1), 175–202.

Nicolo, A., & Pelizzon, L. (2008). Credit derivatives, capital requirements and opaque OTC markets. Journal of Financial Intermediation, 17(4), 444-463.

Olszak, M., Pipień, M., Kowalska, I., & Roszkowska, S. (2017). What Drives Heterogeneity of Cyclicality of Loan-Loss Provisions in the EU?. Journal of Financial Services Research, 51(1), 55-96.

Perez, D., Salas-Fumas, V., & Saurina, J. (2008). Earnings and capital management in alternative loan loss provision regulatory regimes. European Accounting Review, 17(3), 423-445.

Shrieves, R. E., and D. Dahl. (2003). Discretionary Accounting and the Behaviour of Japanese Banks under Financial Duress. Journal of Banking and Finance, 27(7), 1219–1243.

Skała, D. (2015). Saving on a Rainy Day? Income Smoothing and Procyclicality of Loan Loss Provisions in Central European Banks. International Finance, 18(1), 25–46.

Stern, G. (2009). Better Late Than Never: Addressing Too-Big-To-Fail. Brookings Institution, Washington, D.C., March 31.

Stern, G., and R. Feldman. (2009). Addressing TBTF by Shrinking Financial Institutions: An Initial Assessment. Federal Reserve Bank of Minneapolis: The Region, June, 8–13.

Tabak, B. M., Fazio, D. M., & Cajueiro, D. O. (2013). Systemically important banks and financial stability: The case of Latin America. Journal of Banking & Finance, 37(10), 3855-3866.

Warfield, T. D., J. J. Wild, and K. L. Wild. (1995). Managerial Ownership, Accounting Choices, and Informativeness of Earnings. Journal of Accounting and Economics, 20(1), 61–91.

Watts, R., Zimmerman, J., 1986. Positive Accounting Theory. Prentice Hall, Englewood Cliffs, NJ.

White, G. I., Sondhi, A. C., & Fried, D. (2003). The Analysis and Use of Financial Statements 3rd Ed. John Wiley & Sons.

Zimmerman, J. L. (1983). Taxes and Firm Size". Journal of Accounting and Economics, 5, 119–149.

Appendix

A1: Summary of Sample Distribution			
Country	G-SIBs	Non G-SIBs	# Banks
United Kingdom	13	22	35
Germany	2	24	26
Ireland	1	9	10
Luxembourg	2	5	7
Norway	1	6	7
Denmark	1	10	11
Finland	1	3	4
Greece	0	4	4
Portugal	2	4	6
Belgium	1	9	10
Netherland	3	9	12
Sweden	2	9	11
Spain	2	8	10
France	7	28	35
Italy	2	27	29
Austria	1	13	14
Grand Total	41	190	231

A2: List of G-SIBs

Bucket	G-SIBs in alphabetical order within each bucket
5 (3.5%)	(Empty)
4 (2.5%)	HSBC JP Morgan Chase
3 (2.0%)	Barclays BNP Paribas Citigroup Deutsche Bank
2 (1.5%)	Bank of America Credit Suisse Goldman Sachs Mitsubishi UFJ FG Morgan Stanley Royal Bank of Scotland
1 (1.0%)	Agricultural Bank of China Bank of China Bank of New York Mellon BBVA Groupe BPCE Group Crédit Agricole Industrial and Commercial Bank of China Limited ING Bank Mizuho FG Nordea Santander Société Générale Standard Chartered State Street Sumitomo Mitsui FG UBS Unicredit Group Wells Fargo

Appendix A2 provides the list of G-SIBs in 2014 allocated to buckets corresponding to required level of additional loss absorbency. The bucket approach is defined in Table 2 of the Basel Committee document *Global systemically important banks: updated assessment methodology and the higher loss absorbency requirement*, July 2013. The numbers in parentheses are the required level of additional common equity loss absorbency as a percentage of risk-weighted assets that will apply to G-SIBs identified in 2014, starting in January 2016. Available at: http://www.fsb.org/wp-content/uploads/r_141106b.pdf