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European bank loan loss provisioning and technological innovative progress

ABSTRACT:

This paper presents an analysis of Loan Loss Provisioning (LLP) behavior of European banks across 26-member states to determine how bad management and Technological Innovative Progress (TIP) has affected bank risk management. Technological improvements in banking have seen advances in both back and front office operations with respect to lending. This is created through increased disembodied technological change capturing improvements in both non-financial and risk management technologies. We find, using a new dynamic LLP model that European banks employed bad management practices in relation to their lending and monitoring practices, leading to higher losses on loans (through increased LLPs). However, the relationship between TIP and LLPs indicates that those banks which increased their technological efficiency with respect to costs had a greater ability to recognize bad loans, and were therefore able to subsequently increase LLPs. That is, improving technology mitigated the impact of bad management practices in European banks.

Keywords: Loan loss provision accounting; Bad management; Technological innovative progress; Earnings management; Risk management.

JEL Classifications: C33: G01: G28: G21

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1. Introduction

This paper aims to present the first contribution introducing and testing whether technological innovative progress (TIP) and the effects of increases in scale effects associated with TIP (TIPSB) has had an effect on Loan Loss Provisioning (LLP) risk strategies. As Berger (2003) discusses, technological innovation can come about through internet banking, electronic payments systems and information exchanges (e.g., the increase in the number of ATMs – in the UK ATMS have increased year-on-year from 54,900 in 2004 to 69,600 in 2017). Furthermore, increases in TIP can have a positive effect on productivity and scale efficiencies as banks are able to reduce financing costs and risk through the increased use of derivatives and off-balance sheet activities such as securitization, something found recently by Badunenko & Kumbhakar (2017). However, to the best of our knowledge, TIP and TIPSB have not, as yet, become a common determinant in the estimation of dynamic models within the LLP literature. The implication of this is that to date, it has not been tested whether TIP or TIPSB affects the LLP risk behavior of bank management – which we find in this research.

This can be considered an important omission within the current literature concerning the potential relationship between TIP, TIPSB and LLP and needs to be considered. Indeed, as banks have advanced their internal processes associated with IT systems, and better managed their loan portfolios through increased risk management modelling, this gives rise to endogeneity in any empirical specification¹. TIP and TIPSB is therefore an important determinant of the risk management of LLPs in banks and can follow an erratic process over the economic cycle as inputs change due to inventive and innovative progress. In addition, technological advances can also come from external factors including changes in regulation (see Allen & Liu 2007), which are then implemented by banks internally, or through deregulation and increases in competition (see Liu, 2010 and Badunenko & Kumbhakar 2017). For example, the Basel accords which were implemented in our sample period resulted in updates to capital requirements and changed the internal risk management characteristics of banks with respect to LLPs (Basel Committee on Banking Supervision, 2004). This seemingly exogenous effect can be internally compartmentalized into banks LLP risk management business models again leading to endogeneity between TIP and LLP (see, Adrian, 2018).

Furthermore, TIP can be said to be embodied or disembodied and as such, technological change becomes an important characteristic of bank risk management behavior dynamically.

¹ An excellent review of changes in risk management processes and regulations in banks and their effect on bank operations can be found in a recent IMF paper, Adrian (2018).

We posit that technological innovations in LLP risk management can be embodied in the design of information technology (IT), new regulations, and risk management processes, that are used in both back-end and front-end applications. Which we consider has had an effect on how loan portfolios are monitored, and subsequently the risk assessments utilized when agreeing to loans. As Fukuyama and Weber (2015) argue “*financial institutions should be willing to accept nonperforming loans up to the point where the lost income (including principle) on the marginal performing loan is just offset by the reduced monitoring costs or by the increased interest income on the loan portfolio*” (page 46). However, embodied technological change with respect to LLPs is difficult to establish unless the researcher has inside information on the system characteristics of banks’ IT risk arrangements and thereby their IT cost procurements for risk systems over time (as discussed by Berger, 2003).

To circumvent non-reporting of individual bank spending on technological improvements we proxy TIP by the use of estimating technological change through a cost function (this first stage has been undertaken by Hunter & Timme, 1991, Drake & Simper, 2002 and Berger, 2003). Hence, we consider technologies such as information processing (i.e., improved quality in processing deposit and loan customer information), and financial technologies such as, more advance use of risk management statistical techniques (i.e., more efficient future risk evaluation of the loan portfolio) – thus estimating directly disembodied technological change. This so called disembodied technological change therefore provides us with an initial insight to determine whether there are dynamic characteristics that should be considered when analyzing bank LLP risk management behavior (with which we concur).

Finally, our additional contribution is to estimate a comprehensive model that examines the major LLP hypotheses whilst incorporating bad management, TIP and TIPSB in a dynamic second stage specification. However, we have to accept that these additional descriptors with LLP, could be endogenous, thereby leading to problems of estimation in a standard setting. To overcome these problems we follow the approach of system GMM (Arellano & Bover, 1995 and Blundell & Bond, 1998) and we conduct a thorough SGMM with additional post estimation diagnostics not commonly reported in previous LLP empirical literature. Unfortunately, the former problem of finding correct instruments and ensuring that a dynamic LLP model is not over instrumentalized has been misinterpreted in the literature, leading to potentially biased and misleading results, which we aim to address. It should be noted at this point the importance of the Hansen J-statistic and how researchers have misinterpreted the estimate and Roodman’s p-value equal to a 0.25 lower bound (Roodman, 2009b). Indeed, Roodman (2009a) warns against the ‘liberal’ use of conventional significance levels when trying to rule out correlation

between instruments and the error term. For example, Mamatzakis et al. (2013), Table 11, has all 6 models with a Hansen statistic below 0.163, Table 12 with all 4 models below 0.22 and Table 13 with all 5 models having a Hansen below 0.24; Skala's (2015) Models (7) and (8) present p-values equal to 0.17 and 0.03; whereas, Olszak et al. (2016) Table 3 gives actual values ("**** denotes significant at the 1% level") equal to 1343.45**** (Model 3), 1310.45**** (Model 4) and 284.4**** (Model 8), Table 4, Models 2, 3, 5, 6, 7 and 10 all have 'significant at the 1% level', in Table 5, all 13 different models have 'significant at the 1% level' and even in their 'robustness check, Table 9 has 9 of the 12 models all rejecting at the 1% critical level Hansen statistics. Our final contribution is to present a coherent LLP dynamic specification that can therefore explain these numerous theories in a fully specified model.

The remainder of this paper is organized as follows: Section 2 provides a review of previous literature specific to LLP. Section 3 presents our hypotheses. Section 4 provides a detailed justification of our methodological approach with Section 5 discussing the data. Section 6 presents our empirical results and discusses them in the context of both previous studies, with conclusions developed in Section 7.

2. Literature survey of traditional LLP behavior

In an economic downturn the nature of LLPs is an important determinant to be analyzed by regulators. That is, if capital fails to cover the growth of bad loans in a recession there could be a potential feedback into the real economy as banks reduce lending to cover these losses by increasing LLPs. This could ultimately exacerbate a downturn in the business cycle through reduced lending as found in European banks (Bouvatier & Lepetit, 2008). Furthermore, Glen & Mondragón-Vélez (2011) argue, 'understanding these dynamics' is of importance for investors and regulators to determine what effect macroeconomic downturns could have on bank loan portfolios (see also Anandarajan, Hasan, & Lozano-Vivas, 2005) and hence inefficiencies. Indeed, the bad management hypothesis argues that these inefficiencies could be created through poor credit monitoring (use of technology), insufficient control of operating costs, and unstable capital. Given that identified credit losses are absorbed by the specific component of LLPs, managers could have an incentive to increase general LLPs thereby reducing future unidentified risks and their effect on Tier 2 capital. Bad management therefore indicates a negative relationship between efficiency and LLPs and is tested directly in our new model.

Efficiency could also influence future income streams through cost skimming which implies banks cut costs such as loan monitoring and screening for higher short-term profit efficiency. Thus, when banks boost profit efficiency, loan losses could increase in the future, despite an unchanged current level of documented nonperforming loans (NPLs). Therefore, low efficiency could encourage managers to add more general LLPs for future safety whilst not increasing specific LLPs. Cost skimming suggests a likely positive relationship between efficiency and general LLP, but also a lagged relationship with NPL because “as time passes,..., the inaction to the loan portfolio becomes apparent” (Berger & DeYoung, 1997, page 853). Hence, this leads us to posit a dynamic model as previous levels of LLP, through the discretionary component of bank management, has a feedback mechanism to current LLP levels.

The final associated LLP hypothesis states that low efficiency could increase future risk because of moral hazard. In the presence of information asymmetry and agency problems, managers take on more risk which is entirely borne by shareholders and hence engage in risky non-traditional banking services, such subprime lending, to boost profitability (Hughes & Mester, 1998 and Fiordelisi et al. 2011). Moral hazard could therefore be prevalent when banks in the recent regulatory environment, considered themselves to be systemically important and hence ‘too big to fail’ (TBTF)².

Finally, it is also of interest to regulators as to why banks counter or pro-cyclically LLP manage risk, where one such hypothesis relates to how LLPs can be used to manipulate earnings by income smoothing and ultimately a bank’s share price. With respect to economists, they generally regard income smoothing more positively due to reducing the negative impacts of asset volatility across the business cycle, for example, on bank capital (see Anandarajan et al., 2005). Interestingly, contrariwise to economists, accountants regard income smoothing as financial manipulation (Laeven & Majnoni, 2003) whereby managers are able to use their own judgement to influence earnings (through the discretionary component of LLP; Bouvatier & Lepetit, 2008) and hence create problems for shareholders comparing firm profitability and subsequent optimal portfolio share allocations. That is, income smoothing “*introduces judgemental modifications to a firm’s earnings, that also when not induced by personal managers’ objectives, tend to reduce the comparability of results across firms, and may ultimately damage shareholder value*” Laeven & Majnoni (2003), page 197. This, of course, is based on the seminal findings of Litner (1956) in that corporations appear to smooth

² The Royal Bank of Scotland (RBS) was the largest bank globally by total assets in 2008, yet required over £45 billion in emergency government funding in October of that year in an attempt to remain liquid and maintain stability in the UK banking market. It is widely recognised that the majority of the funds issued by the government were used to cover credit write-downs in the ill-fated recently acquired ABN-Amro subsidiary of the business.

dividends relative to earnings. Indeed, reporting stability concerning income streams can signal cost efficiencies and could affect stock price stability and external rating performance, as well as lowering funding costs and increasing management bonuses and salaries (Bikker & Metzmakers, 2005). Income smoothing can also distort efficient markets as complete information on the earnings of banks are not fully known or understood by all market participants; leading to arbitrage opportunities for those who know the income-smoothing practices of a particular bank (see, Fonseca and González, 2008 and Leventis et al. 2011). We next present our hypotheses in relation to efficiencies and technological innovative progress.

3. LLP hypotheses

Hypothesis 1. Technological Innovative Progress (TIP)

Our first measure estimates the percentage change in cost of inputs resulting from changes in bank technology. Our so-called TIP measures are obtained from a Stochastic Frontier cost function (details are provided in Supplementary Appendix A)³. Following Badunenko & Kumbhakar (2017) we estimate TIP holding everything else constant in the cost function equal to $TIP = (\partial \ln C / \partial T)$ where “technical change in a cost function is cost diminution over time” (page 796). If $TIP < 0$, then bank outputs can be produced at a lower total cost as a result of TIP. Given data and the parameter estimates obtained from the cost function, TIP is incorporated into our specification as an individual bank specific variable, $ITIP$. In addition, TIP can be further decomposed into a scale biased technological innovative progress along the ray average cost curve $TIPSB = (\partial \ln C / \partial \ln y \partial T)$. If $TIPSB < 0$, then for a given product mix, TIP causes larger banks to be more efficient over time than their smaller competitors and hence helps to minimize costs (see, Berger, 2003 and Allen & Liu, 2007). That is, after the technological change, production at the previously optimal size (Q) is no longer cost minimizing, and bank size has to increase to Q^* (where $Q^* > Q$) in order to minimize ray average costs. In terms of our model, this again is incorporated through individual bank specific estimates, $ITIPSB$. Given that negative values of TIP ($TIPSB$) imply technological progress, in order to make the regression equation more intuitive, we decompose the two proxies into two separate dummy variables capturing negative and positive values separately.

³ We use the standard Intermediation approach commonly estimated in the literature, see for example, Williams (2004), Allen & Liu (2016) Girardone et al. (2009), Wheelock and Wilson (2012) and Bryce et al. (2015). It is not an aim of this paper to delve into a discussion of the input/output debate on bank modelling.

More specifically, the negative dummy variable takes the value of $ITIP$ ($ITIP_{SB}$) for banks with negative $ITIP$ values ($ITIP_{SB}$) and zero otherwise. Similarly, we introduce a second dummy that takes the value of $ITIP$ ($ITIP_{SB}$) for banks with positive $ITIP$ values ($ITIP_{SB}$) and zero otherwise⁴. These dummies are reported as $ITIP_{<0}$, $ITIP_{>0}$ and $ITIP_{SB<0}$, $ITIP_{SB>0}$ respectively.

Hypothesis 2: Bad Management

We include return on average equity ($roae$), where performance is used as a proxy for the quality of management. This expands on the NPL models of Louzis et al. (2012) where the authors consider a ‘bad management II’ hypothesis using return on equity as a proxy for managerial abilities. In LLP modelling ROE is an uncommon variable but it can show that if banks increase loans (holding inputs constant, e.g., monitoring) then they could see an increase in profitability (efficiency) in the short run. However, in the long run they may experience worse bank performance results, ROE therefore serves as a proxy for poor lending abilities which in turn implies increased levels of LLPs. As Louzis et al. (2012) states “*performance is negatively associated with increases in future NPLs, ..., by regarding past performance as a proxy for the quality of management*” or in our case *LLPs* (page. 1015). To include bad management in our model is an addition to the LLP literature which so far excludes this relevant variable (see, for example, Anandarajan, Hasan & Lozano-Vivas 2005; Fonseca and González, 2008; and Leventis et al. 2011).

Hypothesis 3: Income Smoothing

Bank management may adjust LLPs in order to report stability of income streams over time by increasing (decreasing) the level of LLP when net profits are high (low) in order to minimize variance in earnings. To capture any income smoothing and mitigate for potential endogeneity, we include profit before taxes and provisions scaled by lagged total assets ($oprofit$) (Skala, 2015). This implies that LLPs could increase during periods of economic growth while they decline throughout economic downturns (Bouvatier & Lepetit, 2008). As stated above and to recap, this practice could affect market efficiency through increases in asymmetric information between principle and agent. On the other hand, income-smoothing assumes a positive

⁴ Similar dummy variable has been used by Bouvatier & Lepetit (2008) to capture non-linearity in the relation between LLP and earnings.

connotation for economists since it can be considered as a tool to reduce asset volatility on bank capital across the business cycle (Laeven & Majnoni, 2003).

Hypothesis 4: Capital Management

The capital management hypothesis is tested by the inclusion of total common equity over average assets (*equity*), in which banks manipulate (general) LLPs in order to maintain a particular capital adequacy ratio under Basel I (Basel Committee, 1987), where general LLP are included in Tier 2, albeit subject to strict limits (see, Agarwal et al. 2007). That is, since there is a potentially high cost associated with raising new capital on the market, especially during economic downturns, there is an incentive for banks to manage their capital ratios using general LLP under Basel I (but less so under Basel II).

Hypothesis 5: Business Cycle

The business cycle hypotheses are tested in consideration of the significance of macroeconomic *{Macro}* coefficients which includes GDP growth (*GDPGR*) and unemployment rate (*UNEMP*). If we find a positive GDP growth and negative unemployment rate coefficients, this indicates pro-cyclical managing of LLPs. These are the standard variables utilized in the literature, see for example, Bikker & Metzmakers (2005), Bouvatier & Lepetit (2008) and Bushman & Williams (2012), Ghosh (2007) and Leventis et al. (2011).

Additional Control Variables and Hypotheses of Interest.

As is also common in the LLP modelling literature, we include both bank and industry specific control factors which could affect management behavior towards the manipulation of LLPs. The bank specific controls include a dummy variable taking the value of 1 if the bank is listed to the stock exchange (*listed*) and a size proxy (*SIZE*) expressed as the log of total assets (Pérez et al. 2008). To capture variation in LLP with respect to loan expansions and increased credit risk while controlling for the non-discretionary component of LLP we include a control variable change in the rate of growth of loans (*loansgr*). Forward looking provision implies that banks anticipate that loan growth may results in future NPLs and therefore counter cyclically provision against potential loan losses. A negative relationship between loan growth and LLP points towards lack of prudential provisioning strategies under rapid loan expansion, similar to Bikker & Metzmakers (2005), Fonseca & González (2008) and Skala (2015). We also include Loans to Deposits (*lodep*) as a proxy for liquidity and loan coverage by banks.

In relation to the $\{Industry\ Country\ Controls\}$, we include the industry overall non-performing loans ($INPL$) and following Fujii et al. (2018) we add a dummy variable taking the value of 1 if the country belongs to the EU15 group of countries, and zero otherwise ($EU15$). Finally, we include a dummy that takes the value of 1 for the years 2008-2011 and zero otherwise to capture variations in LLP due to the global financial crisis ($crisis$)⁵.

4. Research design

As a basis for our LLP specification, we posit a relationship such that LLP becomes a function of previous years' LLPs, and its value at time t is likely to be affected by its lagged term. This general specification is given by equation (1).

$$LLP_{it} = \alpha + \sum_{j=1}^J \alpha_j LLP_{it-j} + \beta X_{it} + \eta_i + \varepsilon_{it} \quad (1)$$

Where, LLP is the ratio of loan loss provisions to average loans (as in Anandarajan, Hasan & McCarthy 2007), LLP_{it-j} is the autoregressive component capturing dynamics in the provisioning practices, X_{it} is the vector of explanatory variables capturing income smoothing, capital management, business cycle, bad management, TIP, and bank specific characteristics; η_i are individual bank specific effects; and ε_{it} is an error term and where the subscripts $i = 1, \dots, N$ and $t = 1, \dots, T$ denote the cross sectional and time dimensions of the panel. However, given the inclusion of a lagged dependent variable in the equation to be estimated, the conventional panel data estimators are inconsistent since the unobserved panel-level effects are correlated with the lags of the dependent variable. First differencing (Δ) equation (1) eliminates the individual effects and estimation becomes a straightforward instrumental variables problem, which allows the existence of potentially endogenous right-hand side variables⁶. This general specification is given by equation (2).

$$\Delta LLP_{it} = \sum_{j=1}^J \alpha_j \Delta LLP_{it-j} + \beta \Delta X_{it} + \Delta \varepsilon_{it} \quad (2)$$

⁵ In preliminary analysis we included time fixed effects but were found to be jointly insignificant and consequently we do not include them in the main model. The results were found to be qualitatively the same. The definition for the outset of the global financial crisis follows Curcio et al., (2017). We also included a crisis dummy to capture the years 2008-2014 (and 2009-2014). The results overall remain consistent.

⁶ This is the Anderson and Hsiao (1981) estimator where instruments can be constructed in the form of lagged differences or lagged levels.

Arellano & Bond (1991) propose the use of the Generalized Method of Moments (GMM) procedure taking advantage of all available moment conditions, from which instrumental variables can be drawn from. More specifically, the set of instrumental variables used in the estimation of equation (2) is derived from the following moment conditions, equation (3).

$$E(\mathbf{X}_{it-s}\Delta\varepsilon_{it}) = E(LLP_{it-s}\Delta\varepsilon_{it}) = 0 \dots s > j \quad (3)$$

The above equation suggests that lagged levels of the lagged dependent, and explanatory variables, are used as instruments for the differenced equation. Arellano & Bover (1995) and Blundell & Bond (1998) suggest that variables in levels may be poor instruments for the differenced equation when they are close to a random walk. To mitigate this potential shortcoming, they build a system of equations, consisting of the equation in differences and in levels in a stacked form, equation (4).

$$\begin{bmatrix} LLP_{it} \\ \Delta LLP_{it} \end{bmatrix} = a + \sum_{j=1}^J \alpha_j \begin{bmatrix} LLP_{it-j} \\ \Delta LLP_{it-j} \end{bmatrix} + \beta \begin{bmatrix} \mathbf{X}_{it} \\ \Delta \mathbf{X}_{it} \end{bmatrix} + \varepsilon_{it} \quad (4)$$

The above equation can be estimated as a system and Arellano & Bover (1995) and Blundell & Bond (1998) suggest using lagged levels as well as lagged differences as instruments; covering any potential weakness arising from the Arellano & Bond (1991) estimation technique. Formally, these additional orthogonality conditions can be expressed as, equation (5).

$$E[(\Delta \mathbf{X}_{it-s}(\eta_i + \varepsilon_{it}))] = E[(\Delta y_{it-s}(\eta_i + \varepsilon_{it}))] = 0 \dots s > j \quad (5)$$

The orthogonality restrictions described in equations (3) and (5) provide the underpinnings of the panel data system GMM (SGMM) estimation. Under the assumption of independent and homoscedastic residuals, consistent parameter estimates can be obtained, while controlling for time-invariant unobserved heterogeneity, simultaneity bias and the aforementioned dynamic relationships.

The majority of empirical studies that have adopted the LLP GMM method also consider the dynamics of bank management in a combined hypothesis testing model; see, for example, Laeven & Majnoni (2003), Bouvatier & Lepetit (2008), Fonseca & González (2008), Bryce et al. (2015) and Olszak et al. (2016). Indeed, our model incorporates jointly, bad management, TIP, income smoothing, capital management and business cycle hypotheses, proposing a new model. This is now the preferred approach and circumvents potential problems on the exclusion of relevant variables in hypothesis testing; see (Anandarajan, Hasan, & McCarthy,

2007 and Ghosh 2007). Rewriting equation (1) the specific econometric regression takes the following form, equation (6),

$$\begin{aligned}
 LLP_{it} = & const + \alpha_j \sum LLP_{it-j} + \beta_1 oprofit_{it} + \beta_2 equity_{it} + \beta_3 loangr_{it} \\
 & + \beta_4 loaddep_{it} + \beta_5 roae_{it} + \beta_{6,7} \{ITIP(SB)_{<0;it}\} \\
 & + \beta_{8,9} \{ITIP(SB)_{>0;it}\} + \gamma_{1,2} \{Macro_{it}\} \\
 & + \delta_{1,2} \{Bank\ Specific\ Controls_{it}\} \\
 & + \delta_{3,4} \{Industry\ Country\ Controls_t\} + \varepsilon_{it}
 \end{aligned} \tag{6}$$

In equation (6), the subscripts i and t denote the bank and time dimension of the panel data (we further omit these notations for simplicity). In relation to the variables included in the model, lagged values of the dependent variable capture the autoregressive component in the emergence of doubtful loans, or time series persistency (see Packer & Zhu, 2012). These lags give therefore a closer approximation to the potential impact of stock variables on LLP at time t and lessens the potential problems related to omitted variables (Laeven & Majnoni, 2003). The introduction of lags of the dependent variable also takes into account a change in the speed of adjustment of loan loss provisions and “captures adjustment costs that constrain complete adjustment to an equilibrium level” (Fonseca & González, 2008, page 221). The remaining explanatory variables follow the discussion on Section 3 with their associated hypotheses.

5. The data

Bank-level data was downloaded from BankScope (Fitch-IBCA) over the period 2002 to 2014, hence beginning at the introduction of Euro note circulation (€), with industry/macroeconomic variables obtained from World Bank and SNL Financial. A similar sample period has also been used in Fujii et al. (2018), but the sample of banks has been decreased due to missing data in the dependent variable LLP. Finally, McKee & Kagan, (2018) also utilize a data set ending in 2014 in a study of US community banks. The sample is constructed based on the following rationale; firstly, we are interested in how banks based in member states behave in local markets with respect to LLPs and are therefore not individually influenced by cross-border management behavior from non-domestic bank holding companies

located in another jurisdiction - which of course could be found under a consolidated sample⁷. We therefore follow the methodology of the ‘SYMBOL’ bank stress testing risk assessments published by the European Commission that models risk associated with non-performing loans using only unconsolidated data (Benczur et al., 2017 also follows this procedure). The final sample consists of 450 commercial banks with 3.145 observations, operating in 26 European countries. Table 1 presents the summary statistics of the variables used in our dynamic SGMM for the full sample. (a detailed discussion on the frequency distributions of banks per country and year and a description of asset size classes can be found in Supplementary Appendix B).

INSERT TABLES 1 & 2 HERE

Table 2 presents the correlation matrix for the explanatory variables used in the regression. None of the bank specific variables exhibit very high correlations therefore mitigating any multicollinearity concerns. With respect to the macroeconomic and industry variables, we observe that the reported correlations follow the theoretical expectations and the highest correlation is reported between the unemployment rate (*UNEMP*) and industry non-performing loans (*INPL*), 0.576 (significant at the 5% level). In terms of insignificance – only 15 pairwise correlations were found to show an insignificant relationship between the variables. We next present our results.

6. Empirical results

6.1. Technological Innovative Progress (TIP) Results

Table 3, Panel A reports the results of TIP for each of the 5 quintiles (asset classes) in which frequency indicates the number of banks within each quintile that are negative and significantly

⁷ For example, the European Central Bank supervised entity list shows banks which are supervised on the grounds of different ‘significant asset size’ starting from a bottom class of €30 to €50 billion. For example, in terms of the Spanish bank Banco Santander S.A. (size class above €1,000 billion) it has individual ‘significant size presence’ in Spain, Portugal, Austria, Belgium Germany, Italy and Luxemburg. Whereas, the French bank BNP Paribas (size class above €1,000 billion) has individual ‘significant size presence’ in France, Austria, Belgium, Germany, Italy, Luxemburg, The Netherlands and Portugal. Hence, the use of consolidated accounts could muddy the water concerning which country management risk practice is used overall, say in the home country (Spain or France) against its overseas banks in constituent countries within the European Union. An unconsolidated approach is therefore deemed best to determine the characteristics at the individual country level instead of a Bank Holding Company approach (consolidated) which could not differentiate across and between these interesting country specific management LLP difference practices – again based on the EU SYMBOL approach to analysing banks.

different from zero. With respect to the results we observe that 38.51% of banks experienced overall TIP. In addition, the different subgroups indicate that quintiles 2, 3 and 4 (the small, medium and large banks respectively) experienced greater cost reductions due to TIP than the average sized banks. For example, with respect to quintile 2 (small banks with assets between €280 million and €669 million) had a TIP equal to 51.51% and quintile 3 (medium asset sized banks €670 million to €1,291 million) had the largest TIP equal to 65.82%.

These results show that the small and medium banks appear to be statistically more innovative due to technological change than the largest banks (quintile 5 equal to 11.61%). An explanation for these results is that small and medium sized banks innovate at a faster rate than the largest banks (quintile 5) as the latter can rely on a large customer based and branch network – exploiting market power for profitability. Whereas, smaller banks rely on being agile in the face of innovation to counteract scale inefficiencies (being too small in asset size) to fund operations, reduce capital costs, and implement new technologies to reduce costs.

Interestingly our finding is an update to Berger & Deyoung (2003), who in their analysis between the relationship of the largest MBHCs to smaller affiliates, find that “*MBHCs apply some of the hard-information techniques to small bank affiliates for the first time, yielding substantial increases in control over these affiliates*” (p. 1507) and as such the smallest banks had greater TIP. As we only consider unconsolidated banks our results indicate a standalone size effect of small and medium size asset banks and not a relationship where the largest banks force cost efficiencies on smaller banks through their own innovations. Our results could also show that the smaller banks are playing TIP catch-up with their larger competitors.

With respect to the scale biased results our findings show that overall TIPSB also increased, equal to 44.07%, but this effect is largest in relation to quintiles 1, 2 and 3 and as such these banks were able to increase their efficient size due to TIP (Table 3, Panel B) and hence again reduce costs. The smaller and medium size banks were able to expand operations (outputs) faster than the largest banks due to the introduction of new technology (additional discussion on the distributions of TIP(SB) for different asset sizes can be found in Supplementary Appendix C).

INSERT TABLE 6

Figure 1 (Panels A and B) shows the distributions of TIP and TIPSB in the pre and post-crisis periods (we follow Curcio & Hasan (2015) and define 2008 as the beginning of the crisis). The vertical lines represent the median of the distribution and values less than zero indicate

technological progress. In all panels the thin solid line represents no technological progress. With respect to TIP we observe that banks relied on innovations to reduce their costs more during than after the crisis period (2008-2014). Indeed, we observe a shift in the density distribution towards the left in the post-crisis period. These results compare nicely with Badunenko & Kumbhakar (2017) who found positive technological progress for state banks equal to 2%, and foreign banks equal to 8% which then declined to 0% after re-regulations in India. The difference between the results is that we consider GFC whereas Badunenko & Kumbhakar (2017) review changes in Indian bank regulations. Furthermore, with respect to TIPSB, we note that banks experience size increases due to innovations both in the pre and the post-crisis periods. However, this effect is stronger in the pre-crisis period (represented by the thin-dotted line on the left of the graph) as the post-crisis distribution shifts to the right after 2008 (represented by the long-dash distribution).

INSERT FIGURE 1

The above observations are further examined by presenting only the distributions of the banks that experienced a significant TIP result (Figure 2). Panel A shows this distribution with respect to those banks that exhibit reductions in cost due to technological progress. The post-crisis distribution has a longer left tail than the pre-crisis, indicating greater TIP for the years after the crisis.

INSERT FIGURE 2 HERE

We find that banks increased technological innovations after the crisis by implementing new loan controls, whilst adjusting risk management process through innovations and regulation (for a discussion of changes in risk regulations during our sample period and how banks changed their operations see a recent IMF report, Adrian, 2018). Whereas, Panel B shows the results for the TIPSB and as noted above, the scale effects due to technological innovations fade away in the post-crisis period as the distribution (solid line, Panel B) has shorter left tail, with a higher negative median.

6.2. Results from dynamic LLP Model.

We estimate a first order dynamic panel data model, following the Arellano & Bond (1991), Arellano & Bover (1995) and Blundell & Bond (1998) method of a two-step system GMM estimator (SGMM)⁸. In our model we assume that all macroeconomic/industry control variables are strictly exogenous to individual banks. On the other hand, with respect to the bank specific variables, prior literature does not offer conclusive evidence as to whether or not LLP determinants should be treated as endogenous or exogenous (Skala, 2015). From an economic perspective, endogeneity may arise due to simultaneous determination of LLP and any of the explanatory bank specific variables. For example, LLP and innovations could be simultaneously determined and the direction of correlation could run from LLP to *TIP* (*TIPSB*). That is, if we assume technological innovations are endogenous choice variables for banks and their levels are chosen so as to optimize the reported levels of LLP at t , then the reported LLP levels may in turn effect the future level of innovations that banks are willing to attain⁹. The implication will be a causal effect from the dependent variable to bank innovations. In this case, LLP and technological innovations are simultaneously determined and *TIP* and *TIPSB* should be treated as endogenous regressors and appropriate IVs be constructed and used in estimation. We reject the null hypothesis of a strict exogeneity test (Wooldridge, 2001), confirming that bank innovations are dynamically endogenous to LLP¹⁰.

In determining consistency across the SGMM estimator and following prior literature (Baum, Schaffer, & Stillman, 2003), two post estimation tests are conducted; the Hansen test of joint validity of the instruments and the second order serial correlation (Arellano – Bond), in order to evaluate the correct specifications of the models. The Hansen over identification test confirmed the validity of our instruments and the absence of correlation between the instruments used and the error term in the models (we fail to reject the null hypotheses in all of the model specifications). It should be noted there is no clear rule as to the optimal number of instruments that should be included in a GMM estimator. However, the proposal by Roodman (2009a) concerning the number of instruments and the Hansen J-test p-values are

⁸ To ensure dynamic completeness, we estimate four (4) auxiliary regressions with different subsets of *LLP* lags. We chose the preferred lag specification on the basis of Akaike's/Schwarz's Bayesian information criteria and a Vuong (1989) test. Results are available upon request.

⁹ This process is subject to income smoothing, capital management and pro/counter cyclical provisioning purposes, among others – as implied by equation (6).

¹⁰ Further lag analysis where we regress the current levels and changes of these levels of the bank specific variables on LLP lags, suggests that previous year's LLP levels are negatively (positively) related to levels of $ITIP_{<0}$ ($ITIPSB_{<0}$), confirming the findings of the strict exogeneity test. Results of the strict exogeneity and lag analysis tests are available upon request.

followed. For example, in Model 1, the number of instruments (442) does not exceed the number of groups (450). Second, the p-values obtained from the Hansen J-statistic equal 0.516. In addition, we investigate the relevance of the SGMM instruments based on under-identification tests, following Wintoki, Linck & Netter (2012) (these tests are discussed in more detail in Supplementary Appendix C). Furthermore, we confirm the validity of the SGMM by rejecting the null of no first order serial correlation $AR(1)$ and we fail to reject the null hypothesis of no second order serial correlation $AR(2)$; which indicates a correct model specification. Finally, the finite sample correction proposed by Windmeijer (2005) is implemented, calculating corrected standard errors.

6.2.1. Discussion of results

With respect to the empirical findings, we present results from different estimators that operate under different assumptions. More specifically, we report findings from static OLS/fixed-effects regressions, dynamic OLS and SGMM¹¹. The estimated coefficients from the regressions are presented in Table 4. The results suggest that the LLP ratio is a positive function of its own lag, with significant coefficients equal to 0.28 to 0.58 (columns [1] and [2]). One insight from the dynamic OLS is the importance of past levels of LLP in explaining variations in its current levels (the R^2 increases from 0.18 in the static OLS to 0.62 in the dynamic). This finding suggests that banks are likely to increase their loan provisions if they have already made provisions in the previous year.

INSERT TABLE 4

Hypothesis 1: Technological Innovative Progress (TIP)

With respect to TIP, one insight that becomes clear is that in the absence of technological progress, there is no effect on banks' LLP levels ($ITIP_{>0}$ and $ITIP_{SB>0}$ are insignificant across all 4 models). However, banks that experience technological progress observe two different results. First, $ITIP_{<0}$ is negative and significant in both dynamic models. It is therefore apparent that as banks extend their innovative and technological capabilities with respect to LLP - through their abilities to determine delinquent and problem loans via new innovations - costs decrease through TIP. These reductions could occur from changes in bank's

¹¹ Prior literature has estimated both static and dynamic LLP specifications. For example, Leventis et al., (2012) and Curcio & Hasan, (2015) estimate static models; Bouvatier et al., (2014) estimate a dynamic regression and Laeven & Majnoni (2003) and Curcio et al., (2017) estimate both.

use of better computer risk modelling systems and also regulation – an addition to standard cost efficiencies (see, Adrian, 2018). Even though we find evidence of bad management (hypothesis 4), banks can potentially reduce the costs associated with their bad management practices through the advancing TIP. That is, improving technology mitigates the impact of bad management.¹²

When taking into account the effect that technological innovations have had on the asset size of banks, we observe that $ITIPSB_{<0}$ is positive and significant. This result suggests one of two things, firstly, as bank's cost minimizing scale of outputs increases due to innovations in technology (for example, capturing more markets with new products or geographical expansion thereby increasing lending), banks show an ability to recognize additional risk (see Hunter & Timme, 1991, page 339). They are then able to service the LLP book through the introduction of advanced implementation of computer risk management systems on the loan portfolio (Hunter & Timme, 1991, call this 'production innovations'), leading to higher levels of LLPs. Or, secondly, banks which experience changes in their cost minimizing output scale, report higher LLPs when at the same time report higher pre-provisioning profits, thus strategically amplifying their income smoothing practices. This could show a link between income smoothing and $ITIPSB$. For example, the smallest asset sized banks experience greater scale changes due to technological innovations. Therefore, if the second hypothesis holds, we would expect to find that smaller banks would be more prone to income smoothing. In untabulated results we further test this size hypothesis by re-estimating equation (6) and including an interaction term between $oprofit$ and a size dummy (taking the value of 1 for banks that belong to the first 3 quintiles and zero otherwise). The estimated coefficient of the interaction term is positive but insignificant, offering no support in favor of aforementioned size hypothesis. All other estimated coefficients remain qualitatively similar to the reported ones in Table 4¹³.

Hypothesis 2: Bad Management

We find a negative and significant $roae$ coefficient in all 4 models thereby showing that European banks exhibit bad management by skimping on monitoring and thereby reducing

¹² We also tested the interaction term between $roae$ and $ITIP_{<0}$ and $roae$ and $ITIPSB_{<0}$ (those banks which experienced improvements in technology). Both coefficients on these interaction terms were found to be positive yet insignificant, while the individual effects of $roae$, $ITIP_{<0}$ and $ITIPSB_{<0}$ remained the same and significant as the current model discussed in this section (results are not presented to save space).

¹³ We also used a dummy taking the value of 1 for banks that are smaller than the median of the log of total assets and the results still hold. The interaction term coefficient was positive but still insignificant.

future earnings by diverting cash resources (or profits/dividends) to bolster LLPs in the future to cover bad decisions in the past (also corroborating Louzis et al. 2012). That is, generally, European bank managers show poor abilities to monitor their loan portfolios and offer loans to people who are likely to default in the event of a macroeconomic downturn. This result ties in nicely with the negative and significant relationship between *GDPGR* and LLP explained in the business cycle hypothesis.

Hypothesis 3: Income Smoothing

The income-smoothing hypothesis concerns the relationship between net income (*oprofit*) and LLP, where we find a significant positive relationship in all estimated regressions (the coefficient ranges from 0.478 in the SGMM to 0.231 in the dynamic OLS). This finding is similar to the results across 40 countries by Fonseca and González (2008), European banks by Leventis et al. (2011), South East Asian countries by Packer & Zhu (2012), central European banks by Skala (2015) and US banks by Balasubramanian et al. (2016). Such that, “regardless of the commendable or condemnable motives underlying income smoothing” (as shown by a positive relationship) “this behavior contributes to financial soundness of banks and reduces procyclicality” (page. 150, Bikker & Metzmakers, 2005). In addition, the drop in the estimated coefficient of *oprofit* when moving from the static OLS to the dynamic OLS implies that current pre-provisioning profits are correlated with past LLP levels, suggesting a potentially endogenous relationship. When controlling for endogeneity and fixed effects under a SGMM, we note that the estimated coefficient doubles in magnitude (equal to 0.4780, Table 4, column [1]). This result therefore suggests that ignoring endogeneity and LLP dynamics could understate the economic significance of income smoothing. Therefore, if *oprofit* is thought to have at least a predetermined effect on LLP then a SGMM approach should be estimated.

Hypothesis 4: Capital Management

With respect to the capital management hypothesis, *equity* the sign of the estimated coefficient remains unchanged across all models (negative), but its significance changes in the static fixed-effects model (significant at the 10%). However, this significance could be an artifact of endogeneity as previous years LLPs are related to levels and hence changes in levels of equity. That is, when taking into account bank specific effects and endogeneity in the SGMM, the results indicate that European banks do not boost their Tier 2 capital positions

using LLPs, and as such, do not suffer from a “banking system capitalization (*problem, which*) is a barrier to business cycle vulnerability” (Glen & Mondragón-Vélez, 2011, page 158, *our italics*). A result also found for Indian banks by Ghosh (2007) and European banks by Leventis et al. (2012).

Hypothesis 5: Business Cycle

We find that there is a negative and significant relationship with *GDPGR* (GDP growth) ranging from -0.0477 in the GMM model, to -0.0292 in the static OLS model. Therefore, European banks did not undertake ‘forward looking’ provisioning, a result corroborated by the negative association between credit growth (*loangr*) and LLP. The implication is that when loan portfolios expand during booms, managers decrease reserves, thus not accounting for possible future losses. This result corresponds favorably with the implementation of IAS39 across Europe. Implying that objective evidence is required on loan impairments before loan loss provisions can be made, hence restricting buffering across the economic cycle and exacerbating pro-cyclical LLP.

In addition, Craig (2005) observes that banks in developed countries (i.e., Australia, Hong Kong, Japan, New Zealand and Singapore) generally show a tendency of assessing risk over relatively short horizons, leading them to under-estimate risk during boom periods while over-estimating the risk during economic downturns. If this was also to be true for European banks our results explain the cancelling out of LLP across the business cycle. However, as Skala (2015) notes, our finding “prompts the question of whether the reserves that central European banks established during economic booms are sufficient” (page. 35). Furthermore, this result could of course be due in part to overriding macroeconomic conditions in our sample period. That is, there was no need to forward provision as banks had different risk management behavior characteristics. To this end, the unemployment rate (*UNEMP*) is found to be insignificant with respect to LLP in all models, see also Bikker & Metzmakers (2005) and Olszak et al. (2016). A possible explanation here, is that the unemployment rate does not act as a proxy for loan demand (Beatty & Liao, 2011). The effect of unemployment is therefore minimal and hence we find an insignificant relationship between the unemployment rate, bank lending and LLPs. This relationship between unemployment and LLP is not a forward-looking relationship, but a current reactionary co-movement: unemployment increases \rightarrow loan defaults increases \rightarrow LLP increases.

Additional Control Variables and Hypotheses of Interest

In addition, our findings highlight that *INPL* (industry non-performing loans) and *lodep* (loans to deposits) do not have significant effects on LLPs, and therefore, industry bank characteristics and individual bank liquidity constraints do not override risk management behavior characteristics. Interestingly, in all specifications there is a negative and significant link between the EU15 status and loan provisions. That is, *ceteris paribus*, banks who operate in the EU15 countries provision less for bad loans, with respect to their non EU15 counterparts. The projected LLP values from the estimated SGMM regression for non EU15 and EU15 countries are 0.0120*** and 0.0096*** respectively¹⁴. With respect to the additional control variables, the dummies *listed* (those banks which are listed on their domestic stock exchanges) and *crisis* (the global financial crisis of 2008) are both insignificant. Finally, with respect to the control variable *SIZE*, this has a negative effect on LLP in all models, indicating that the largest European banks report lower LLPs suggesting that their credit portfolio diversification leads them to report lower provisioning levels.

6.2.2. Additional analyses

Table 5 presents 3 additional SGMM specifications that consider whether our results are stable if we exclude *ITIP* and *ITIPSB*, analyse post crisis income smoothing and also a non-linear income smoothing model following Balboa, López-Espinosa, & Rubia, 2013. In terms of our first robustness check, in Model 1, we can see that removing *ITIP* and *ITIPSB* has no effect on all the hypotheses 1 to 5 above, everything holds albeit we do note that *SIZE* and *crisis* now become significant. Given that *crisis* could potentially offer an insight, we again re-estimate our main SGMM but now Model 2 controls for increased income smoothing during the financial crisis (see for example, Curcio, De Simone, & Gallo, 2017). To investigate for increased income smoothing during the crisis, relative to the pre-crisis period, we include an interaction term *crisis* × *oprofit*. Column [2] in Table 5 reports the estimated coefficients. Most of the estimated coefficients remain similar to those reported in Table 4 column 1, however the *EU15* dummy turns insignificant. With respect to *crisis* × *oprofit*, a one-sided t-test does not confirm the hypothesis that banks have smoothed their income via LLPs more intensively during or after the crisis.

INSERT TABLE 5

¹⁴ 95% confidence intervals were estimated using the Delta method, where *** indicates significance at the 1%.

The third set of additional analysis considers a potential non-linear effect of income smoothing, as incentives to smooth income may be dependent of the relative size of earnings (see, Balboa, López-Espinosa, & Rubia, 2013). In this latter case we generate a dummy variable (*doprofit*) taking the value of *oprofit* for banks reporting pre-provisioning earnings greater than the annual 75th percentile and zero otherwise¹⁵. In Model 3 we find that the coefficient of *doprofit* is positive and significant at the 1%, indicating that the best performing EU banks are more prone to report higher LLPs when earnings are high (Table 5, Column [2]). Once again we find that all hypotheses 1 to 5 are unaffected and the remaining coefficients maintain their sign and significance in line with Table 4, Column [1].

7. Conclusions

In the banking loan loss provisioning literature there has been widely different reported managerial behavior characteristics including; income smoothing, capital management, business cycle theory, and bad management hypotheses. The latter's effect can originate from three sources of inefficiency; cost, technological innovative progress (TIP) and scale based TIP (TIPSB). We present a coherent and fully specified dynamic models that find both bad management, TIP and TIPSB are endogenous with respect to LLP risk management behavior. That is, previous studies which have only explicitly allocated banks' income smoothing, capital management as the internal change characteristic in provisioning behavior could be mis-specified through the exclusion of bad management, TIP and TIPSB.

With respect to our results we find that 38.51% of banks experienced overall TIP but that small banks with assets between €280 million and €669 million had a TIP equal to 51.51% and medium asset sized banks €670 million to €1,291 million had the largest TIP equal to 65.82%. These results show that small and medium asset sized banks are more innovative due to technological progress than the largest banks (assets greater than €1,137, TIP equal to 11.61%). In addition, when we consider scale biased effects, again the smallest banks show the largest

¹⁵ This dummy is a variation used by Bouvatier & Lepetit (2008) as here we are interested in identifying the best performing banks in our sample and not simply the ones reporting positive earnings. We also control for non-linearity in the earning's smoothing around the zero threshold by including a dummy variable taking the value of *oprofit* in the case of positive earnings before provisions and taxes, and zero otherwise. The results are qualitatively similar to the ones reported in Table 9, Column [3] so we do not present them here. Including both *oprofit* and *doprofit* led to VIF values of 85.68 and 85.24 respectively, thus we chose not include both variables together.

TIPSB equal to 58.51% whereas the largest banks showed the smallest TIPSB equal to 20.51%. That is, *ceteris paribus*, the larger banks have smaller scale TIPSB efficiencies relative to smaller banks and therefore smaller to medium banks see larger cost efficiencies in the introduction of new technologies.

The main findings associated with our new LLP model show that as banks extend their innovative and technological capabilities with respect to LLP, costs decrease through TIP. These reductions could occur from changes in bank's use of better risk modelling of their loan portfolios and also through new regulations such as Basel capital requirement directives. In addition, even though we find bad management practice, banks can potentially reduce these costs through advancing TIP. That is, the introduction of new technology and the improvements that it brings mitigates the impact of bad management and its associated cost inefficiencies.

With respect to the traditional LLP hypotheses, we concur that banks income smooth, although profits are correlated with past LLP levels, suggesting a potentially endogenous relationship. European banks do not boost their Tier 2 capital positions using LLPs, and as such, do not suffer from a banking system capitalization. Further, these banks did not undertake 'forward looking' provisioning, a result corroborated by the negative association between credit growth and LLP. Finally, we find that the macro environment had little to no effect as European banks did not undertake 'forward looking' provisioning corresponding favorably with the implementation of IAS39 across Europe limiting the pro-cyclical nature of LLPs.

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Table 1. Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
<i>LLP</i>	3,145	0.0101	0.0314	-0.2610	1.2379
<i>oprofit</i>	3,145	0.0151	0.0172	-0.0531	0.7081
<i>equity</i>	3,145	0.0999	0.0718	-0.0029	0.8620
<i>loansgr</i>	3,145	0.0772	0.3085	-0.9879	8.7691
<i>GDPGR</i>	3,145	0.0121	0.0330	-0.1481	0.1190
<i>UNEMP</i>	3,145	0.0818	0.0326	0.0340	0.2720
<i>roe</i>	3,145	0.0624	0.2592	-8.0755	1.0438
<i>ITIP</i> _{<0}	3,145	-0.0081	0.0172	-0.1766	0
<i>ITIPSB</i> _{<0}	3,145	-0.0032	0.0050	-0.0230	0
<i>ITIP</i> _{>0}	3,145	0.0211	0.0298	0	0.1722
<i>ITIPSB</i> _{>0}	3,145	0.0043	0.0053	0	0.0222
<i>SIZE</i>	3,145	6.8930	1.3556	3.7446	10.754
<i>INPL</i>	3,145	0.0480	0.0468	0.0008	0.4487
<i>lodep</i>	3,145	1.2601	1.6074	0.0202	25

Summary statistics of the variable included in the estimation of equation (6).

Table 2. Pairwise Correlation Matrix

	<i>LLP</i>	<i>oprofit</i>	<i>equity</i>	<i>loangr</i>	<i>GDPGR</i>	<i>UNEMP</i>	<i>roae</i>	<i>ITIP</i> _{<0}	<i>ITIPSB</i> _{<0}	<i>ITIP</i> _{>0}	<i>ITIPSB</i> _{>0}	<i>SIZE</i>	<i>INPL</i>	<i>lodep</i>
<i>LLP</i>	1													
<i>oprofit</i>	0.0595*	1												
<i>equity</i>	-0.0334*	0.2596*	1											
<i>loangr</i>	-0.0602*	0.1025*	0.0386*	1										
<i>GDPGR</i>	-0.1069*	0.1081*	0.0195	0.1546*	1									
<i>UNEMP</i>	0.0948*	-0.0423*	-0.0137	-0.0474*	-0.1459*	1								
<i>roae</i>	-0.2871*	0.2305*	0.00870	0.0720*	0.2036*	-0.1099*	1							
<i>ITIP</i> _{<0}	-0.0887*	0.0206	-0.0296*	0.0162	0.0920*	-0.00430	0.0418*	1						
<i>ITIPSB</i> _{<0}	0.0657*	-0.0233	-0.0829*	-0.0907*	-0.2349*	0.1067*	-0.0671*	-0.2515*	1					
<i>ITIP</i> _{>0}	-0.0483*	-0.0469*	0.0626*	0.00280	0.0458*	-0.0244	0.0365*	0.3403*	-0.2638*	1				
<i>ITIPSB</i> _{>0}	0.0173	-0.0483*	-0.0613*	-0.1097*	-0.1479*	0.1900*	-0.0645*	-0.1136*	0.5356*	0.1063*	1			
<i>SIZE</i>	-0.0709*	-0.0542*	-0.3063*	0.00400	-0.0465*	-0.0225	0.0750*	-0.00400	0.3150*	0.1089*	0.3376*	1		
<i>INPL</i>	0.1153*	-0.0306*	-0.0391*	-0.1046*	-0.3237*	0.5767*	-0.1854*	-0.0525*	0.2394*	-0.0230	0.3082*	-0.0109	1	
<i>lodep</i>	-0.00220	0.0272	0.1843*	-0.0163	-0.0502*	0.0375*	-0.0447*	-0.2843*	0.0246	-0.00340	0.00820	-0.0512*	0.0303*	1

Pearson's correlation coefficients

* Statistically significant at 10%

Table 3. TIP and TIP scale biased results

Panel A TIP	Frequency (significant TIP)	Average TIP (%)	Total observations
Quintile 1 – Smallest	71	11.29	629
Quintile 2 – Small	324	51.51	629
Quintile 3 – Medium	414	65.82	629
Quintile 4 – Large	329	52.31	629
Quintile 5 – Largest	73	11.61	629
Overall	1,211	38.51	3,145
Panel B TIPSB	Frequency (significant TIPSB)	Average TIPSB (%)	Total observations
Quintile 1 – Smallest	368	58.51	629
Quintile 2 – Small	358	56.92	629
Quintile 3 – Medium	313	49.76	629
Quintile 4 – Large	218	34.66	629
Quintile 5 – Largest	129	20.51	629
Overall	1,386	44.07	3,145

Frequency: Number of observations with negative technological progress and negative scale biased technological progress. The table suggests that 51.51% of small sized banks experienced technological progress (Panel A, Quintile 2). The asset size of banks belonging in the five quintiles presented here are discussed in detail in Supplementary Appendix B.

Table 4. Results of Loan Loss Provisioning Identification

	Dynamic Models		Static Models		
	SGMM	Pooled OLS with lag	Pooled OLS	VIF	Fixed Effects
<i>LLP</i> ($t - 1$)	0.2801*** (0.0802)	0.5880*** (0.149)			
<i>oprofit</i>	0.4780*** (0.155)	0.2310** (0.107)	0.2930** (0.133)	1.16	0.2880*** (0.110)
<i>equity</i>	-0.0404 (0.0284)	-0.0203 (0.0148)	-0.0229 (0.0184)	1.21	-0.136** (0.0614)
<i>loangr</i>	-0.0016 (0.0049)	-0.0003 (0.0019)	-0.0029 (0.0023)	1.06	-0.0025 (0.0019)
<i>GDPGR</i>	-0.0477*** (0.0142)	-0.0360*** (0.0135)	-0.0292** (0.0146)	1.43	-0.0355*** (0.0129)
<i>UNEMP</i>	0.0544 (0.0523)	0.0320 (0.0334)	0.0642 (0.0725)	1.56	-0.0172 (0.0482)
<i>roae</i>	-0.0351*** (0.0072)	-0.0356*** (0.0059)	-0.0444*** (0.0069)	1.15	-0.0434*** (0.0074)
<i>ITIP</i> _{<0}	-0.0917** (0.0369)	-0.0599* (0.0340)	-0.0713 (0.0544)	1.32	-0.0106 (0.0393)
<i>ITIPSB</i> _{<0}	0.3170** (0.144)	0.2910*** (0.100)	0.417*** (0.138)	2.31	0.298 (0.250)
<i>ITIP</i> _{>0}	0.0344 (0.0352)	0.00230 (0.0144)	0.0087 (0.0158)	1.38	-0.0263 (0.0610)
<i>ITIPSB</i> _{>0}	-0.0682 (0.117)	-0.0583 (0.0809)	-0.0469 (0.117)	2.15	0.0013 (0.172)
<i>SIZE</i>	-0.0020*** (0.0007)	-0.0009* (0.0004)	-0.0022*** (0.0003)	1.42	-0.0033 (0.0045)
<i>INPL</i>	0.0016 (0.0198)	-0.0138 (0.0148)	0.0073 (0.0271)	2.03	0.0500** (0.0197)
<i>lodep</i>	-0.0001 (0.0003)	-0.0002 (0.0002)	-0.0004 (0.0005)	1.15	-0.0017 (0.0017)
<i>crisis</i>	0.0012 (0.0008)	-0.0002 (0.0008)	0.0013 (0.0011)	1.56	0.0006 (0.0008)
<i>EU15</i>	-0.0024* (0.0013)	-0.0025*** (0.0010)	-0.0035*** (0.0013)	1.29	-0.0222 (0.0193)
<i>listed</i>	0.0002 (0.0010)	0.0009 (0.0007)	0.0014 (0.0009)	1.05	0.0433* (0.0231)
<i>constant</i>	0.0179*** (0.0069)	0.0123** (0.0057)	0.0242*** (0.0072)		0.0480 (0.0393)
<i>N</i>	3145	3145	3195		3195
<i>R</i> ²		0.622	0.187		0.218
<i>Robust Hausman test (p-value)</i>					0.000
<i>AR(1) test (p-value)</i>	0.000				
<i>AR(2) test (p-value)</i>	0.957				
<i>Lags</i>	2-4				
<i>IV count (groups)</i>	442 (450)				
<i>Hansen test of overidentification (p-value)</i>	0.516				
<i>Underidentification test for differenced equation</i>	0.0078				
<i>Underidentification test for levels equation</i>	0.0220				

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Windmeijer (2005) robust standard errors reported. For brevity, we report only the key diagnostics here. A detailed description of the additional statistics is presented in Supplementary Appendix D. *AR(1)* and *AR(2)* are tests for first and second order serial correlation, under the null hypothesis of no serial correlation. The 'lags' show the number of lags used in the GMM model for bank specific variables. The Hansen test of overidentification is under the null that all instruments are valid.

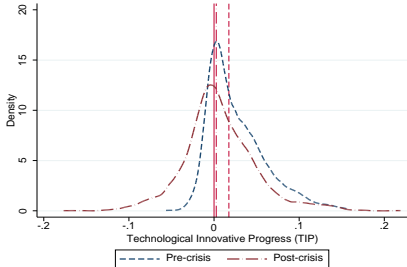
Table 5. Additional Analyses

	Model 1 Without Tech Change	Model 2 Post Crisis Income smoothing	Model 3 Non-Linear Income Smoothing
<i>LLP</i> ($t - 1$)	0.2550*** (0.0776)	0.2890*** (0.0774)	0.2670*** (0.0798)
<i>oprofit</i>	0.6390*** (0.1650)	0.5080*** (0.1640)	
<i>crisis</i> × <i>oprofit</i>		0.0133 (0.147)	
<i>doprofit</i>			0.3006*** (0.0690)
<i>equity</i>	-0.0513 (0.0343)	-0.0456 (0.0297)	-0.0371 (0.0268)
<i>loangr</i>	-0.0015 (0.0050)	-0.0014 (0.0052)	0.0015 (0.0052)
<i>GDPGR</i>	-0.0529*** (0.0162)	-0.0415** (0.0183)	-0.0390*** (0.0132)
<i>UNEMP</i>	0.0500 (0.0559)	0.0511 (0.0536)	0.0517 (0.054)
<i>roae</i>	-0.0395*** (0.0087)	-0.0357*** (0.0073)	-0.0344*** (0.0068)
<i>ITIP</i> _{<0}		-0.0831** (0.0332)	-0.0855** (0.0383)
<i>ITIPSB</i> _{<0}		0.3170** (0.1490)	0.3820** (0.1570)
<i>ITIP</i> _{>0}		0.0328 (0.0376)	0.0427 (0.0351)
<i>ITIPSB</i> _{>0}		-0.0639 (0.108)	-0.156 (0.123)
<i>SIZE</i>	0.0005 (0.0014)	-0.0021*** (0.0008)	-0.0018** (0.0007)
<i>INPL</i>	0.0087 (0.0211)	0.0089 (0.0238)	0.0067 (0.0196)
<i>lodep</i>	0.0003 (0.0004)	-0.0001 (0.0004)	0.0001 (0.0003)
<i>crisis</i>	0.0023** (0.0011)	0.0012 (0.0024)	0.0005 (0.0008)
<i>EU15</i>	-0.0027** (0.0013)	-0.0005 (0.0028)	-0.0027** (0.0012)
<i>listed</i>	-0.0008 (0.0013)	-0.0031 (0.0035)	0.0007 (0.0009)
<i>constant</i>	-0.0004 (0.0120)	0.0168*** (0.0063)	0.0212*** (0.0072)
<i>N</i>	3145	3145	3145
<i>AR(1) test (p-value)</i>	0.000	0.000	0.000
<i>AR(2) test (p-value)</i>	0.919	0.945	0.828
<i>Lags</i>	2-6	2-4	2-4
<i>IV count (groups)</i>	390 (450)	442 (450)	443 (450)
<i>Hansen (p-value)</i>	0.290	0.470	0.511
<i>Year Effects</i>	Insignificant	Insignificant	Insignificant

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Windmeijer (2005) robust standard errors reported. *AR(1)* and *AR(2)* are tests for first and second order serial correlation, under the null hypothesis of no serial correlation. The 'lags' show the number of lags used in the GMM model for bank specific variables. Our results hold under different lag choices. The Hansen test of overidentification is under the null that all instruments are valid.

Figure 1. Distributions of Technological Change and Scale Biased Technological Change: pre and post-crisis - Vertical lines represent the median. Values less than zero indicate technological progress

Panel A: Technological Innovative Progress (TIP)



Panel B: Technological Innovative Progress Scale Biased (TIPSB)

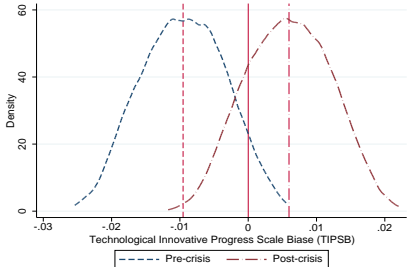
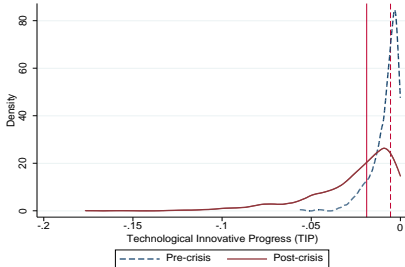


Figure 2. Distributions of banks exhibiting technological progress and scale biased technological progress - Vertical lines represent the median

Panel A: Technological Innovative Progress (TIP)



Panel B: Technological Innovative Progress Scale Biased (TIPSB)

