Macroprudential Policy,
Countercyclical Bank Capital Buffers and Credit Supply:
Evidence from the Spanish Dynamic Provisioning Experiments

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Abstract

We analyze the impact of countercyclical capital buffers held by banks on the supply of credit to firms and their subsequent performance. Spain introduced dynamic provisioning unrelated to specific bank loan losses in 2000 and modified its formula parameters in 2005 and 2008. In each case, individual banks were impacted differently. The resultant bank-specific shocks to capital buffers, coupled with comprehensive bank-, firm-, loan-, and loan application-level data, allow us to identify its impact on the supply of credit and on real activity. Our estimates show that countercyclical dynamic provisioning smooths cycles in the supply of credit and in bad times upholds firm financing and performance.

JEL Codes: E51, E58, E60, G01, G21, G28.
Key words: bank capital, dynamic provisioning, credit availability, financial crisis.

I. INTRODUCTION

In 2007 the economies of the United States and Western Europe were overwhelmed by a banking crisis, which was followed by a severe economic recession. This sequence of events was not unique: Banking crises are recurrent phenomena and often trigger deep and long-lasting recessions (Reinhart and Rogoff (2009); Schularick and Taylor (2012)). A weakening in banks' balance-sheets usually leads to a contraction in the supply of credit and to a slowdown in real activity (Bernanke (1983)). Moreover, banking crises regularly come on the heels of periods of strong credit growth (Kindleberger (1978); Bordo and Meissner (2012); Gourinchas and Obstfeld (2012)). To analyze credit availability in both good and bad times is thus imperative.

The damaging real effects associated with financial crises has generated a broad agreement among academics and policymakers that financial regulation needs to acquire a macroprudential (henceforth, "macropru") dimension that ultimately aims to lessen the potentially damaging negative externalities from the financial to the macroeconomic real sector, as for example in a credit crunch. Countercyclical macropru policy tools could be used to address these cyclical vulnerabilities in systemic risk, by slowing credit growth in good times and especially by boosting it in bad times.[1] Under the new international regulatory framework for banks – Basel III – regulators agreed to vary minimum capital requirements over the cycle, by instituting countercyclical bank capital buffers (i.e., procyclical capital requirements). As part of the cyclical mandate of macropru policy the objective is that in booms capital requirements will increase while in busts requirements will decrease, thus increasing the buffers of capital that banks have when a crisis hits.

Introducing countercyclical bank capital buffers aims to achieve two macropru objectives at once. First, boosting equity or provisioning requirements in booms

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[1] Countercyclical capital tools such as procyclical capital requirements (countercyclical capital buffers) that deal with the procyclicality of the financial system is the common terminology we follow. The systemic orientation of the macropru approach contrasts with the orientation of the traditional micropru approach to regulation and supervision, which is primarily concerned with the safety and soundness of the individual institutions. For example the deleveraging of a bank after a negative balance-sheet shock may be optimal from a micropru point of view, but the negative externalities of the deleveraging through the contraction in the supply of credit to the real sector may impose real costs on the broad economy that macropru – but not micropru – policy considers. Borio (2003) and Hanson, Kashyap and Stein (2011) discuss regulatory tools. See also Bernanke (2011), Kashyap, Berner and Goodhart (2011), Yellen (2011a) and Goodhart and Perotti (2012).

provides additional buffers in downturns that help mitigate credit crunches. Second, higher requirements on bank own funds can cool credit-led booms, either because banks internalize more of the potential social costs of credit defaults (through a reduction in moral hazard by having more "skin in the game") or charge a higher loan rate due to the higher cost of bank capital.[2] Countercyclical bank capital buffers could therefore lessen the excessive procyclicality of credit, i.e., those credit supply cycles that find their root causes in banks' agency frictions.[3] Smoothing bank credit supply cycles will generate positive firm-level real effects if bank-firm relationships are valuable and credit substitution for firms is difficult in bad times.

Despite the hurried attention now given by academics and policymakers alike to the global development of macropru policies, *no* empirical study so far has estimated the impact of a macropru policy tool on the *supply of credit* and on real activity. This paper aims to fill this void by analyzing for the first time a series of pioneering policy experiments with dynamic provisioning in Spain:[4] From its introduction in 2000 and modification in 2005 during good times, to its amendment and reaction in 2008 when a severe (mostly unforeseen) crisis shock struck causing bad times.[5] The policy experiments coupled with comprehensive bank-, firm-, loan-, and loan application-level data provide for an almost ideal setting for identification.

Dynamic provisions – initially also called "statistical" later on "generic" provisions as a statistical formula is mandating their calculation that is not related to bank-

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[2] See Morrison and White (2005), Adrian and Shin (2010), Shleifer and Vishny (2010b), Tirole (2011), Adrian and Boyarchenko (2012), Jeanne and Korinek (2012) and Malherbe (2012). Tax benefits of debt finance and asymmetric information about banks' conditions and prospects imply that raising external equity finance may be more costly for banks than debt finance (Tirole (2006), Freixas and Rochet (2008), Aiyar, Calomiris and Wieladek (2011) and Hanson, Kashyap and Stein (2011)). An increase in capital requirements will therefore raise the cost of bank finance, and thus may lower the supply of credit. Admati, DeMarzo, Hellwig and Pleiderer (2010) question whether equity capital costs for banks are substantial.

[3] The cycles in credit growth consists of periods during which the economy is performing well and credit growth is robust (on average 7 percent) and periods when the economy is in recession or crisis and credit contracts (on average -2 percent) (Schularick and Taylor (2012)). Credit cycles stem from either: (i) banks' agency frictions (credit supply) as in e.g. Rajan (1994), Holmstrom and Tirole (1997), Diamond and Rajan (2006), Allen and Gale (2007), Shleifer and Vishny (2010a), Adrian and Shin (2011), and Gersbach and Rochet (2011), or (ii) firms' agency frictions (credit demand) as in e.g. Bernanke and Gertler (1989), Kiyotaki and Moore (1997), Lorenzoni (2008), and Jeanne and Korinek (2010).

[4] We customarily designate these changes in policy as "experiments", though macro-policy shocks to the banking sector are never (intentionally) randomized and banks dealing with different types of borrowers may be differentially affected. Therefore, both shocks and comprehensive data are necessary for identification.

[5] Good times dramatically turned into bad times in Spain in 2008. Before 2008 GDP growth was always more than 2.7 percent during our sample period (in 2002 it was 2.7 percent, while in Germany GDP contracted by 0.4 percent in 2003 and in the US growth was merely 1.1 percent in 2001). In 2007 GDP in Spain grew by 3.6 percent and in 2008 it still grew by 0.9 percent. After 2008 Spain experienced a severe recession: GDP contracted with 3.7 percent in 2009 and the unemployment rate jumped to more than 25 percent.

specific losses – are forward-looking provisions, which before any credit loss is recognized on an individual loan build up a buffer (i.e., the dynamic provision fund) from retained profits in good times that can then be used to cover the realized losses in bad times (i.e., those times when specific provisions surpass the average specific provisions over the credit cycle). The buffer is therefore counter-cyclical. The required provisioning in good times is over and above specific average loan loss provisions and there is a regulatory reduction of this provisioning (to cover specific provision needs) in bad times, when bank profits are low and new shareholders' funds through for example equity injections are costly. Dynamic provisioning has been discussed extensively by policy makers and academics alike,[6] and dynamic provision funds are now considered to be Tier-2 regulatory capital.

The two policy experiments in good times we study are: (1) The introduction of dynamic provisioning in 2000:Q3, which by construction entailed an additional non-zero provision requirement for most banks, but – and this is crucial for our estimation purposes – with a widely different formula-based provision requirement across banks; and (2) The modification that took place in 2005:Q1, which implied a net modest loosening in provisioning requirements for most banks (i.e., a tightening of the provision requirements offset by a lowering of the ceiling of the dynamic provision fund).

We also investigate one policy experiment in bad times: (3) The reduction in provisioning requirements by the sudden lowering of the floor of the dynamic provision funds in 2008:Q4 from 33 to 10 percent (such that the minimum stock of dynamic provisions to be held at any time equals 10 percent of the latent loss of total

[6] See Section 2 and the Appendix, and Fernández de Lis, Martínez Pagés and Saurina (2000), Saurina (2009a) and Saurina (2009b) for detailed treaties on *dynamic* provisioning, and Fernández de Lis and Garcia-Herrero (2010) on the more recent experiences in Columbia and Peru. On October 27, 2011, the Joint Progress Report to the *G20* by the *Financial Stability Board*, the *International Monetary Fund* and the *Bank for International Settlements* on "Macroprudential Policy Tools and Frameworks" featured dynamic provisions as a tool to address threats from excessive credit expansion in the system. On November 11, 2011, Yellen (2011b) discussed dynamic provisions in a Speech on "Pursuing Financial Stability at the Federal Reserve". See also reports from the *Bank for International Settlements* (Drehmann and Gambacorta (2012)), the *Eurosystem* (Burroni, Quagliariello, Sabatini and Tola (2009)), the *Federal Reserve System* (Fillat and Montoriol-Garriga (2010)), the *Financial Services Authority* (Osborne, Fuertes and Milne (2012)), discussions in for example *The Economist* (March 12, 2009), the *Federation of European Accountants* (March 2009), the *Financial Times* (February 17, 2010; June 15, 2012), *JP Morgan* (February, 2010), the *UK Accounting Standards Board* (May, 2009), etc., and academic work by Shin (2011) and Tirole (2011) for example. Laeven and Majnoni (2003) find evidence that banks around the world delay provisioning for bad loans until it is too late, when cyclical downturns have already set in, thereby magnifying the impact of the economic cycle on banks' income and capital. Dynamic provisioning increases provisioning in good times, so that the banks' need for new own funds (capital) in bad times is lower.

loans) that allowed for a greater release of provisions (and hence a lower impact on the profit and loss of the additional specific provisions made in bad times). Concurrent with the third policy experiment, and following the (mostly unforeseen) crisis shock in 2008:Q3, we analyze *ceteris paribus* the workings of the dynamic provision funds built up by the banks as of 2007:Q4, i.e., we investigate how existing bank buffers perform during the crisis period.

To identify the availability of credit we employ a comprehensive credit register that comprises loan (i.e., bank-firm) level data on *all* outstanding business loan contracts, loan applications for non-current borrowers, and balance sheets of all banks collected by the supervisor. We calculate the total credit exposures by each bank to each firm in each quarter, from 1999:Q1 to 2010:Q4. Hence the sample period includes six quarters before the first policy experiment (essential to run placebo tests) and more than two years of the financial crisis. We analyze changes in committed credit volume, on both the intensive and extensive margins, and also credit drawn, maturity, collateral and cost. By matching with firm balance sheets and the register for firm deaths, we can also assess the effects on firm-level total assets, employment and survival.

Depending on their credit portfolio (i.e., the fraction of consumer, public sector and corporate loans mostly) banks were differentially affected by the three policy experiments. Therefore, we perform a difference-in-difference analysis where we compare before and after each shock differently affected banks' lending at the same time to the same firm (Khwaja and Mian (2008); Jiménez, Mian, Peydró and Saurina (2011); Jiménez, Ongena, Peydró and Saurina (2012)). Though we analyze the same bank before and after the shock, we further control for up to 32 bank variables and also key bank-firm and loan characteristics.

In good times, for the first two policy experiments that take place, we find that banks that have to provision relatively more (less) cut committed credit more (less) to the same firm after the shock – and not before – than banks that need to provision less (more). These findings also hold for the extensive margin of credit continuation and for credit drawn, maturity, collateral, and credit drawn over committed (as an indirect measure of the cost of credit). Hence, procyclical bank capital regulation in good times cuts credit availability to firms.

Results are robust to numerous perfunctory alterations in the specification (e.g., adding bank and loan characteristics and firm * bank type fixed effects), the sample (e.g., restricting it to firms with balance sheet information), and the level of clustering of the standard errors (e.g., multi-clustering at the firm and bank level).

Even though for the first policy experiment for example we apply the dynamic provision formula to each bank's credit portfolio in 1998:Q4, rather than in 2000:Q3 when the policy became compulsory for all banks, wonted endogeneity concerns could linger. Policy makers capable of accurately predicting the aggregate and especially heterogeneous changes in bank credit could have devised the formula to maximize the credit impact for example. In that case excluding either the savings banks (that are often of direct interest to politicians) or the very large banks (i.e., four banks that represent almost 60 percent of all bank assets), and instrumenting realized bank provisions with the deterministic formula-based provisioning on the basis of banks' past loan portfolios (shown not to be a weak instrument) allays any remaining endogeneity concerns as the estimates are not affected.

But are firms really affected in good times by the average shock to the banks that they were borrowing from before the shock? We find mostly not. Though total committed credit received by firms drops somewhat immediately following the introduction of dynamic provisioning (and commensurately increases following its modification), three quarters after the policy experiments there is no discernible contraction of credit available to firms. Consistently we find no impact on firm total assets, employment, or survival, suggesting that firms find ample substitute credit from less affected banks (both from new banks and from banks with an existing relationship) and from other financiers.

Yet, while firms overall are not significantly affected, there are noteworthy changes in credit allocation. For example the negative impact of higher provisioning requirements on credit is stronger for smaller banks (which may struggle more to absorb the capital shock) and smaller firms (which may be more bank dependent), but weaker for lowly-capitalized firms (*sic*). The latter finding suggests that higher capital requirements not only cut credit, but may also shift it to potentially riskier firms (e.g., Martinez-Miera (2008), Illueca Munoz, Norden and Udell (2013)).

In bad times things look very different. Banks with dynamic provision funds close to the floor value in 2008:Q4 (and hence that benefited most from its lowering in the third policy experiment) and banks with ample dynamic provision funds just before the crisis hit permanently maintain their supply of committed credit to the same firm after the shock at a higher level than other banks. Similar findings hold for credit continuation, drawn and drawn over committed (i.e., at a lower cost of credit). At the same time these banks shorten loan maturity and tighten collateral requirements, possibly to compensate for the higher risk taken by easing credit volume during the crisis.

Results are again robust to alterations in the specification, the sample, the level of clustering of the standard errors, and to the exclusion of the very large banks. Importantly, given that more cautious banks could choose levels of provisioning higher than the ones stemming from regulation, the results are robust to the instrumentation of the (potentially endogenous) dynamic provision funds in 2007:Q4 with the formula-based dynamic provision funds required for the bank's portfolio for as far back as 2000:Q3 (when dynamic provisioning was introduced)!

Even more strikingly different in bad times than in good times is that the changes in loan level credit are binding at the firm-level, i.e., credit permanently contracts especially for those firms that borrowed more from banks that benefitted less from the policy experiment (by being far above the floor value) or that when the crisis hit had lower dynamic provision funds. Hence, firms seemingly cannot substitute for the lost bank financing. Consistent with this interpretation we find that firm total assets, employment, or survival are negatively affected as well.

The estimates are also economically relevant. Following the floor-lowering experiment, firms with banks in the lowest quartile above the floor obtain a 6 percentage points higher credit growth and a 0.7 percentage point higher total asset growth. Following the crisis shock, firms with banks with a 1 percentage point higher dynamic provision funds (over loans) prior to the crisis get a 10 percentage points higher credit growth, a 2.5 percentage points higher asset growth, a 2.7 percentage points higher employment growth, and a 1 percentage point higher likelihood of survival.

Substituting a bank is markedly more difficult in bad times than in good times. Indeed, we find that the granting of loan applications to non-current borrowers in bad times is almost 30 percent lower than in good times and that a 1 percentage point lower dynamic provision funds (over loans) leads to a 9.4 percentage points lower likelihood that a loan application by a non-current borrower will be accepted and granted. In sum, banks with higher capital buffers stemming from the stricter regulatory requirements in good times partly mitigate the deleterious impact of the financial crisis on the supply of credit, both for their current and non-current borrowers.

But there are further notable differences across banks and firms. For both the third policy experiment (the one in bad times) and the crisis shock, credit growth is weaker at banks with higher non-performing loan ratios, as in bad times such banks likely face a higher market capital requirement. In contrast, for the third policy experiment, smaller and lowly-capitalized firms obtain relatively more credit, while for the crisis shock firms with a better credit history and a longer banking relationship benefit most. This suggests that banks that are in the lowest quartile above the floor (on dynamic provision funds) may gamble for resurrection when the floor is lowered (i.e., stemming from lowering capital requirements for the lowly capitalized banks), while banks that are well provisioned when hit by the crisis seemingly continue to make judicious lending choices. These findings suggest that to ensure financial stability macropru policy should increase capital requirements in good times for all banks, rather than reducing them in bad times for the lowly-capitalized ones.

In sum, responding to the urgent interest among policymakers and academics, ours is the first empirical paper to actually estimate the impact of a macropru policy on credit supply cycles.[7] The evidence is robust and shows that countercyclical bank capital buffers can mitigate cycles and can have a positive effect on firm-level and aggregate financing and performance. In bad times switching between lowly- and

[7] Differences with the extant bank capital literature are many. (1) We study policy experiments that exogenously change the regulatory capital requirements in good and bad times and the workings of countercyclical capital buffers when a crisis hits. In contrast, Peek and Rosengren (2000) and Puri, Rocholl and Steffen (2011), among others, exploit the negative shocks to the profitability of multinational banks that occur abroad and that affect actual bank capital. (2) We identify the supply of credit with a difference-in-difference analysis of loan- and loan application-level data. Bernanke and Lown (1991), Berger and Udell (1994) and Cornett, McNutt, Strahan and Tehranian (2011), Gambacorta and Mistrulli (2004), Carlson, Hui and Warusawitharana (2011), among others, rely on a panel, VAR or matching analysis of bank-level data. (3) We assess the impact on bank-firm level credit availability, maturity, collateralization, and cost, and on firm-level financing and performance. Hubbard, Kuttner and Palia (2002), Berger and Bouwman (2009), Ashcraft (2006), Mariathasan and Merrouche (2012), Mora and Logan (2012) and Berger and Bouwman (2013), among others, assess bank-level credit growth or cost, and liquidity creation and performance. (4) We analyze not only the average effect on credit but also the differences that occur across banks and firms, in particular with respect to possible risk-taking. We also study the real effects. Both risk-taking and the externalities to the real sector may ultimately be more important for financial stability than the topics dealt with in the extant bank capital literature so far.

highly-capitalized banks is difficult and firms will be more affected by capital shocks. Procyclical capital regulation will therefore spur lending and deliver positive real effects in bad times, though lowly-capitalized banks may also engage in some additional risk-taking then.

The rest of the paper proceeds as follows. Section II discusses dynamic provisioning in detail. Section III introduces the data and identification strategy. Section IV presents and discusses the results. Section V concludes by highlighting the relevant implications for theory and policy.

II. DYNAMIC PROVISIONS AS A COUNTERCYCLICAL TOOL

1. Countercyclical Capital Tool

The recent financial crisis has been the worst since the great depression. As such, it has spurred many policy discussions among governments, central banks, as well as financial regulators and supervisors. In parallel, it has opened a debate on how to best prevent the next crisis. When analyzing the proposals for achieving this last objective, there seems to be a widespread consensus among both academics and policy makers on the need for enhancing macropru policies. The idea is that it is not enough to monitor the individual solvency of banks. There is an additional need for the monitoring of the endogenous risk-taking by banks (during credit booms), and there is the potential for very strong negative externalities from banks to the real sector in crisis' times. In sum, systemic risk needs to be confronted and for that purpose, macropru instruments are needed. The frontier between micro and macropru instruments is sometimes blurred, but the distinction comes mainly at the level of the objectives being achieved (i.e., stability at the level of each institution versus stability of the whole banking system and its relation with the real sector).

Among macropru instruments, the ones that have attracted most interest are countercyclical tools. G20 meetings have stressed the importance of mitigating the procyclicality of the financial system (i.e., lending booms and busts that exacerbate the inherent cyclicality of lending, and consequently distort investment decisions, either by restricting access to bank finance or by fuelling credit booms).[8]

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[8] For instance, the G20 at the Summit held in Washington requested Finance Ministers to formulate specific recommendations on mitigating procyclicality in regulatory policy (G20 (2008)). Furthermore, the G20

The intuition for a countercyclical capital tool is that banks should increase their capital in good times and reduce them in bad times. A higher level of requirements in expansions should contribute to moderate lending. A lowering of capital requirements in bad times should reduce the incentives of banks to cut additionally their lending and, therefore, to worsen the recession. This is precisely the macro dimension of a regulatory tool (capital requirements in this example) or, in short, a macropru tool.

Despite all the interest and discussion on macropru policies and, in particular, on countercyclical policies and tools, there is almost no real experience on how these instruments may work along a business/lending cycle. Most of the discussions are theoretical or assessments that are numerically simulated;[9] except for one case: Dynamic provisions in Spain. Enforced since 2000:Q3,[10] they are a countercyclical instrument, intended to increase loan loss provisions in good times to be used in bad times.

2. *Dynamic Provisioning*

Dynamic provisions are a special kind of general loan loss provisions. Recall that provisions made by banks can be specific or general. The former are set to cover impaired assets, that is, incurred losses already identified in a specific loan. General provisions, on the contrary, cover losses not yet individually identified, that is, latent losses lurking in a loan portfolio, which are not yet materialized on a particular loan. Therefore, general provisions are very similar from a prudential point of view to bank capital, which is in a bank to cover future losses that may materialize in their assets.

In case of liquidation of a bank, general provisions correspond to shareholders (i.e., there is no other stakeholder that can claim them). Therefore, as dynamic provisions (as said) are a special kind of general loan loss provision, the buffer they accumulate in the expansion phase can be assimilated to a capital buffer. From 2005 onwards,

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Pittsburgh Summit called on Finance Ministers and Central Bank Governors to commence "building high-quality capital and mitigating procyclicality" (G20 (2009)). The Financial Stability Board issued in April 2009 a series of reports recommending that the Basel Committee should make appropriate adjustments to dampen the excessive cyclicality of the minimum capital requirements (FSB (2009)). Treasury Secretary Geithner (2009), Chairman Bernanke (2009) and Chairman Turner (2009) advocated that capital regulation should be revisited to ensure that it does not induce excessive procyclicality.

[9] Repullo, Saurina and Trucharte (2010) provide a counterfactual simulation exercise with a countercyclical capital buffer. See also Fei, Fuertes and Kalotychou (2012) for related simulations.

[10] We take 2000:Q3 as the first quarter of the introduction, as the new law in 2000:M7 was followed by the enforcement at the end of 2000:M9.

dynamic provisions were also formally considered to be Tier-2 capital (regulatory capital, although not as core as shares).

The formulas that determine the dynamic provisioning requirements in Spain are simple and transparent (see Appendix). Total loan loss provisions in Spain are the sum of: (1) Specific provisions based on the amount of non-performing loans at each point in time; plus (2) a general provision which is proportional to the amount of the increase in the loan portfolio and; finally plus (3) a general countercyclical provision element based on the comparison of the average of specific provisions along the last lending cycle (for the whole banking sector) with the current specific provision (for each individual bank).

This comparison is precisely what creates the countercyclical element: In good times, when non-performing loans are very low, specific provisions are also very low and in comparison with the average of the cycle provisions, the difference is positive and the dynamic provision funds is being build up. In bad times, the opposite occurs: Specific provisions surge, as a result of the increase in non-performing loans, and the countercyclical component becomes negative drawing down the dynamic provision funds.

In addition to the formula parameters, there are floor and ceiling values set for the fund of general loan loss provisions, to guarantee minimum and avoid excess provisioning, respectively. Banks are also required to publish the amount of their dynamic provision each quarter.

3. *Three Policy Experiments in 2000, 2005 and 2008 and the Crisis Shock in 2008*

In 2000:Q3 dynamic provisioning was introduced in Spain (our first policy experiment) as Spain had very low levels of provisioning compared to the rest of the OECD countries. Following the introduction of the International Financial Reporting Standards (IFRS) in Spain (as in other European Union countries), in 2005:Q1 the parameters of the dynamic provision formula were modified (our second policy experiment), loosening the provisioning requirements. In 2008:Q4 the floor value was lowered from 33 to 10 percent (our third policy experiment), in order to allow an almost full usage of the general provisions previously built in the expansionary period.

The period of analysis in this paper allows us to see the behavior and the impact of dynamic provisions along a full cycle: From 2000 to 2008 Spain went through an impressive credit expansion and from 2008 onwards has been suffering the consequences of the worst recession in more than 65 years. In addition to the three policy experiments and to assess its countercyclical conduct we analyze the workings of dynamic provisions built up by the banks as of 2007:Q4 after the (mostly unforeseen) crisis shock in 2008:Q3.

Spain is indeed very well suited to test whether macropru instruments have an impact on the lending cycle and on real activity. In 1999 Spain had the lowest ratio of loan loss provisions to total loans among all OECD countries, but – as a consequence of the introduction of dynamic provisioning – prior to the crisis in 2008 it had among the highest.

4. *The Macropru Dimension of Dynamic Provisioning*

Even simple time-series plots of total, specific and general provisions already vividly illustrate the macropru dimension of dynamic provisioning in Spain. Figure 1 shows the flow of net loan loss provisions (specific plus general) for Spanish deposit institutions. Before the introduction of dynamic provisions in mid-2000, the total loan loss provisions showed a slightly decreasing trend. Once the countercyclical provision was implemented, the trend in provisions was clearly reversed and the net loan loss provisions went from less than 0.5 to more than 1 billion euros. Although the policy modification in 2005 involved a clear reduction in provisioning requirements, the changes introduced then did not change the previously existing trend until the financial crisis shock, where non-performing loans (and hence specific provisions) started to increase significantly. By the end of 2008 the impact of the crisis becomes apparent as net loan loss provisions increase substantially.

Figure 2 shows the stocks of provisioning in relative terms (i.e., as the percentage of total credit to the private sector). The flow of specific provisions (over total loans granted), i.e., the slopes at various points of time in the figure, represented a very small share of credit exposures (around 0.05 percent) during the expansion years, while the flow of general provisions were more than twice that figure during the same period. Though we cannot differentiate between general and specific provisions before mid-2000, we can observe the two policy shocks in 2000 and 2005, and we can observe how before the crisis the change in the total provisions runs parallel to the change in the general provisions.

However, in 2008, due to the crisis shock, a deep and rather sharp change took place in the lending cycle, and specific provisions increased very rapidly, while general provisions moved into negative territory: The net effect therefore a much less pronounced increase in total provisions. Note that the decrease in the floor value for the general provision fund (i.e., the stock) by the end of 2008 (from 33 to 10 percent) also allowed for a more intense usage of the dynamic provision funds (i.e., these funds were drawn down more intensely) which explain why their flows become much more negative in relative terms.

Figure 2 precisely illustrates the countercyclical nature of dynamic provisioning. If Spain would have had only specific provisions, these would have jumped in two years from less than 0.5 percent of total credit to around 2.5 percent, precisely at a time when bank profits and bank equity issuance are scarce! However, current total provisions have evolved from a minimum of around 1.5 percent of total loans during the lending boom to a level a bit higher than 2.5 percent during the crisis. Loan loss provisions have increased significantly – but to a lesser extent – because of the countercyclical mechanism. This implies that banks used a 1 percent buffer of general loan loss provisions in the crisis at a moment in which profits and equity issuance is scarce and expensive, i.e., those Tier 2 funds that were built-up in the good times where bank profits are significant and equity issuance is cheaper. This is the macroprudential dimension of dynamic provisioning.

In terms of total loans, the countercyclical loan loss provisioning smoothed the total loan loss provision fund coverage. The specific provision fund relative to total loans increased close to 500 percent from 2008 to 2010, whereas the total loan loss provision fund in relation to total loans increased only by 66 percent (or in terms of euros, 50 percent lower than the increase in specific provisions) as a result of the application of the general provisions set up for this purpose. Again, this shows the macropru aspect of dynamic provisions, which in relative terms still increase during recessions. The changes in dynamic provisioning which are the three policy experiments studied in this paper, i.e., the introduction in 2000, the modification in 2005, and the lowering of the floor of the dynamic provision funds in 2008, as well as the 2008 crisis shock (the deepest recession in Spain in more than 65 years) appear clearly in the figure.[11]

III. DATA AND IDENTIFICATION STRATEGY

The identification strategy we detail in this section, that combines comprehensive bank-, firm-, loan-, and loan application-level data with the three policy experiments and a crisis shock, allows us to establish rigorously whether macropru instruments have an impact on the lending cycle and on real activity. As far as we know, this is the first assessment of a countercyclical instrument based on real data along a full credit and business cycle using exogenous shocks.

1. Datasets

In this subsection we discuss the datasets that we employ to underpin our identification strategy. Spain offers an ideal experimental setting for identification; not only because of the policy experiments that took place with dynamic provisioning, but also since its economic system is bank dominated and its exhaustive banking credit register records all relevant bank lending activity. Banks continue to play a key role in the Spanish economy and in the financing of the corporate sector. Prior to the global financial crisis, in 2006 for example their deposits (credits) to GDP equaled 132 percent (164 percent). Most firms had no access to bond financing and the securitization of commercial and industrial loans is still very low (4.8 percent in 2006) (Jiménez, Mian, Peydró and Saurina (2011); Jiménez, Ongena, Peydró and Saurina (2012)).

The exhaustive bank loan data, we have access to, comes from the Credit Register of the *Banco de España* (CIR), which is the supervisor in Spain of the banking system. We analyze the records on the granted business loans present in the CIR, which contains confidential and very detailed information at the loan level on virtually all loans granted by all banks operating in Spain. In particular, we work with commercial

[11] Another interesting point is the final impact on the profit and loss account. The impact of the flow of general provisions on net operating income was material, being around 15 percent during the period before the general provision fund started to be used. This explains why banks were not much in favor of them in the expansionary phase. When dynamic provisions are used (i.e., when the general fund is being drawn down), the impact on net operating income is also very significant and close in terms of relative magnitudes, helping banks to protect their capital during recessions and, therefore, their ability to support lending to households and firms.

and industrial (C&I) loans (covering 80 percent of total loans), granted to non-financial publicly limited and limited liability companies by commercial banks, savings banks and credit cooperatives (representing almost the entire Spanish financial system). We use all the business loans that correspond to more than 100,000 firms and 175 banks in the database in any given year.

The CIR is almost comprehensive, as the monthly reporting threshold for a loan is only 6,000 Euros. Given that we consider only C&I loans, this threshold is very low which alleviates any concerns about unobserved changes in bank credit to small and medium sized enterprises. We match each loan both to selected firm characteristics (in particular firm identity, industry, location, the level of credit, firm size, age, capital, liquidity, profits, tangible assets, and whether or not the firm survives) and to bank balance-sheet variables (size, capital, liquidity, NPLs, profits and other relevant variables). Both loan and bank data are owned by the *Banco de España* in its role of banking supervisor. The firms' dataset is available from the Spanish Mercantile Register at a yearly frequency (and covers a substantial subset of firms in the CIR).

We study not only changes in credit volume (intensive margin) and loan conditions, but also credit continuation and granting of loan applications (extensive margins). For the latter investigation we rely on a database containing loan applications between 2002:M2 and 2010:M12 (detailed by Jiménez, Ongena, Peydró and Saurina (2012)). For each application we also observe whether the loan is accepted and granted, or not, by matching the loan application database with the CIR database, which contains the stock of all loans granted on a monthly basis. Our sample then consists of loan applications by non-financial publicly limited and limited liability companies to commercial banks, savings banks and credit cooperatives.

2. *Identification Strategy*

We first study the policy experiments in good times, i.e., the introduction of dynamic provisions in 2000:Q3 and its modification in 2005:Q1, then turn to the bad times with the policy experiment in 2008:Q4 and the crisis shock. In both good and bad times, we study the impact of the shocks on firm credit availability (average and heterogeneous effects) and performance.

Recall that dynamic provisioning requirements follow an identical formula applied to all the banks that states how much each bank has to provision depending on its credit portfolio. There is an increase of dynamic provisions when current bank specific loan loss provisions are lower than the average value over the cycle of these provisions (which is identical for all banks) and there is a decrease when the value is higher. Given that banks´ specific loan loss provisions are highly correlated with the business cycle and countercyclical, it implies that in good times there are increases in provisioning requirements, and in bad times there are reductions, as explained in detail in Section II (and Appendix).

The formula is identical for all banks as it is based on two sets of six parameters that vary across different loan portfolios. Hence depending on the loan portfolio as well as its current specific loan loss provisions and, indirectly, its non-performing loans, at any moment in time banks will face different provisioning conditions. By the same token banks will also be differently affected by the three policy experiments and by the crisis shock. For each shock we calculate the change in each bank's provisioning requirement. Our analysis then consists of three parts:

(1) For the <u>first policy experiment</u> in 2000:Q3 we apply the provisioning formula that is introduced to the existing loan portfolio in 1998:Q4 – we go back two years to avoid self-selection problems, i.e., banks changing their credit portfolio weights before the law enters into force – yielding a bank-specific amount of new funds that is expected to be provisioned (for some banks with very high current specific provisions the increase in requirements was zero). We then scale this amount by the bank's total assets. We label this scaled amount in provisions for bank *b*, *Dynamic Provision*$_b$, abbreviated in interaction terms by DP_b (Table 1 contains all variable definitions).

(2) For the <u>second policy experiment</u> in 2005:Q1, and in contrast to the previous case, it is problematic to directly calculate the policy-driven changes in dynamic provisioning as there were changes in the ceiling of the dynamic provision funds and change in the parameters of the formula. We therefore instrument the change in yearly provisions (scaled by total assets) with a proxy for the effective policy changes in the formula. In this way we again obtain a bank-specific change in provisioning that is policy driven, again labeled *Dynamic Provision*$_b$.

(3) For the <u>third policy experiment</u> we exploit the lowering in 2008:Q4 of the floor of provision funds which affected mostly the banks with the lowest provision

funds. Our variable in this case is whether or not the bank is in the lowest quartile in terms of provision funds in 2008:Q3, i.e., a variable *d(<25% Dynamic Provision Funds)* that equals one if the bank is in the lowest quartile, and equals zero otherwise, in interaction terms labeled *d(<25%* DPF_b*)*. For the concurrent crisis shock we calculate how much each bank had built up as dynamic (general) provision fund prior to the onset of the crisis (2007:Q4), again scaled by total assets. We label the variable *Dynamic Provision* $Funds_b$, in interaction terms labeled DPF_b. The lower the built-up provision fund *ceteris paribus* the more intensely the bank will be hit by the unexpected crisis shock in 2008, as more profits or equity will be needed to absorb loan losses and to continue lending at the same level.

Since all shocks have bank-specific effects that differ according to the banks' credit portfolio, the shocks cannot be considered "random", and therefore, the data and empirical strategy are crucial. We perform a difference-in-difference analysis where we compare the lending of the same bank before and after each shock and simultaneously compare it to other banks differently affected by the shock – the identification comes *both* from the timing (before and after the shock) and from the shocks that affected banks differentially.

Moreover, despite that we analyze the same bank before and after the shock (i.e., it is like controlling for bank fixed effects in the level of credit), we need to control for other key fundamentals of the bank that could be – potentially – differently affected at the same point of time. First, the borrowers are potentially different and we analyze the change in credit availability to the same firm and the same time by banks with different (treatment) intensity to each shock by using firm or firm-time fixed effects in loan-level regressions (Khwaja and Mian (2008); Jiménez, Mian, Peydró and Saurina (2011); Jiménez, Ongena, Peydró and Saurina (2012)). In this way, we capture both observed and unobserved time-varying heterogeneity in firm fundamentals (i.e., captures credit demand and as firms often engage similar banks also the characteristics of the bank's portfolio composition). Second, we further control for up to 32 bank variables covering all relevant characteristics of banks and, moreover, given that loans from different banks to the same firm and the same time could be different, we also control for key bank-firm and loan characteristics.

To address any remaining endogeneity concerns we further exclude either the savings banks or the very large banks (as policy makers could have devised the formula to maximize the credit impact at either one of these groups of banks), instrument the dynamic provision variable of interest in each experiment with pertinent formula-determined prior values, and add bank fixed effects in cross-sectional specifications that assess the cross-firm impact of bank characteristics.

For the three policy shocks estimates are almost identical either with or without instrumentation, likely because in both cases we rely on the exogenous formula that rules dynamic provisioning. A key variable to instrument is the pre-crisis dynamic provision buffers of 2007:Q4 that we exploit in conjunction with the crisis shock of 2008. Given that more cautious banks could choose levels of provisioning higher than the ones stemming from regulation, we analyze whether the results are robust to the instrumentation of the (potentially endogenous) dynamic provision funds in 2007:Q4 with the deterministic formula-based dynamic provision funds required for the bank's portfolio for as far back as 2000:Q3 (the moment banks provisioned for this first time under the new regulation; as the instrument does not take into account any further specific provisioning in any quarter by any bank it truly determined in 2000:Q3).

Moreover, since firms can substitute credit across different banks, we construct a firm-level measure of susceptibility to bank shocks by averaging the different treatment intensity of the banks that were lending to the firm before each shock, and weight each bank by its *ex ante* credit exposure to the firm. In this way we analyze the impact of bank shocks to firm-level credit availability and real effects. In this firm-level analysis we only control for firm observable characteristics since we cannot use firm fixed effects. However, if there are no statistical differences in the loan-level regressions between the estimates from specifications that include firm fixed effects and those including firm characteristics, then the latter firm-level estimates will not be biased (Jiménez, Mian, Peydró and Saurina (2011)). We also test whether firms turn to less-affected but already-engaged banks (i.e., on the intensive margin) or to for-them "new" banks (i.e., on the extensive margin).

3. *Estimated Models*

a. *Loan-Level Models*

For each of the three parts in the analysis, the benchmark model at the loan level (which will be Model 6 in the Tables 3, A.2, and 6 that will contain the estimated coefficients) we estimate is:

$$\begin{aligned} &\Delta log\ Commitment(impact\ period)_{bf} \\ &\qquad = \delta_f + Bank\ Dynamic\ Provisioning(basis\ period)_{bf} \\ &\qquad + controls_{bf} + \varepsilon_{bf} \end{aligned} \tag{1}$$

where $\Delta log\ Commitment(impact\ period)_{bf}$ is the change (on the intensive margin) in the logarithm of (strictly positive) committed credit by bank *b* to firm *f*,[12] and δ_f are firm fixed effects. $Bank\ Dynamic\ Provisioning(basis\ period)_{bf}$ are the bank-specific dynamic provisioning variable(s) for each bank *b* that grants credit to firm *f* for each policy experiment and the crisis shock, i.e., *Dynamic Provision*$_b$ for the first and second policy experiments, and in the third part of the analysis *d(<25% Dynamic Provision Funds)*$_b$ and *Dynamic Provision Funds*$_b$ for the third policy experiment and crisis shock, respectively. The $controls_{bf}$ include other bank and bank-firm relationship characteristics, and ε_{bf} is the error term.

The impact periods are: (1) 2000:Q1 to 2001:Q2; (2) 2004:Q4 to 2006:Q2; and (3) 2008:Q1 to 2009:Q4, respectively. The basis periods when the bank dynamic provisioning variables are calculated are: (1) The introduction of dynamic provisioning in 2000:Q3 on the basis of the lending portfolio of the banks in 1998:Q4; (2) the changes in dynamic provisioning introduced in 2005:Q1 as reflected in the changes in the dynamic provisioning by banks from 2004:Q4 to 2005:Q2; and (3) the lowering of the floor in 2008:Q4 for banks in the lowest quartile in terms of dynamic provision funds in 2008:Q3, and the crisis shock in 2008:Q3 given the banks' dynamic provision funds in 2007:Q4. The benchmark model will be estimated for a sample of firms with both multiple bank-firm relationships and available firm (balance-sheet) characteristics (to make an adequate comparison with the

[12] We winsorize this dependent variable and *Δlog Drawn* at the 1st and 99th percentile.

corresponding benchmark firm-level specification introduced in the next subsection possible). Standard errors will be clustered at the bank level (clustering at the bank *and* firm level yields virtually identical results).

In robustness we will study consecutively: (a) Different pertinent combinations of other bank, bank-firm relationship, and loan characteristics, and province and industry, firm, and firm * bank type (i.e., commercial, savings and other bank) fixed effects, and different samples, i.e., all bank-firm relationship loans and/or all loans with or without firm characteristics available; (b) Varying impact periods (i.e., quarter by quarter time-varying coefficients); (c) Different dependent variables, i.e., the change in the logarithm of credit drawn, whether or not loans were granted, and the changes in maturity, collateralization, and cost of the loans.

b. Firm-Level Models

For each of the three parts in the analysis, the corresponding benchmark model at the firm level (which will be Model 15 in Tables 3 and 6, and Model 14 in Table A.2) we estimate is:

$$\begin{aligned} \Delta log\ Commitment(impact\ period)_f \\ &= \delta_p + \delta_i + Bank\ Dynamic\ Provisioning(basis\ period)_f \qquad (2) \\ &+ controls_f + \ \varepsilon_f \end{aligned}$$

where $\Delta log\ Commitment(impact\ period)_f$ is the change in the logarithm of (strictly positive) committed credit by *all* banks to firm *f*, δ_p and δ_i are the province and industry fixed effects, $Bank\ Dynamic\ Provisioning(basis\ period)_f$ are the same dynamic provisioning variable(s) as before for all banks that were lending to the firm *f* prior to the shock (weighting each bank value by its loan volume to firm *f* prior to the shock over total bank loans taken by this firm), and $controls_f$ include other bank, bank-firm relationship and firm characteristics for all banks of firm *f*, and ε_f is the error term. Note that the credit that is obtained after the shock can be from "new" banks as well (i.e., that are not borrowed from prior to the shock). Hence we analyze whether firms are able to absorb the impact of the shock (to the banks they were borrowing from prior to the shock) by obtaining more credit from both currently engaged and/or new banks. The impact- and basis periods, and sample, will be the same as for the loan-level analysis, and the standard errors will be clustered at the main bank level.

In robustness we will study consecutively: (a) Different pertinent combinations of other bank, bank-firm relationship, firm and loan characteristics, and different samples, i.e., all firms without firm characteristics available; (b) Varying impact periods; (c) Different dependent variable, i.e., the change in the logarithm of credit drawn. Finally, we also analyze the real effects, in particular the change in firm total assets and of the number of employees, and the impact on the probability of firm death.

c. Loan Application-Level Model

For each firm that seeks to borrow from banks it is currently not borrowing from, we also study the acceptance and granting of all the loan applications the firm made. For each of the three parts in the analysis, the corresponding benchmark model (which will be Model 20 in Tables 3 and 6, and Model 19 in Table A.2) we estimate is:

$$\begin{aligned} &\mathit{Loan\ Application\ Is\ Accepted\ and\ Granted}(\mathit{impact\ period})_{bf} \\ &\qquad = \delta_{ft} + \mathit{Bank\ Dynamic\ Provisioning}(\mathit{basis\ period})_{bf} \\ &\qquad + \mathit{controls}_{bf} + \varepsilon_{bf} \end{aligned} \tag{3}$$

where $\mathit{Loan\ Application\ Is\ Accepted\ and\ Granted}(\mathit{impact\ period})_{bf}$ equals one if the loan application is accepted and granted by bank b to firm f (which is currently not borrowing from the banks it applied to) during the impact period, and equals zero otherwise. δ_{ft} are firm-time fixed effects and $\mathit{Bank\ Dynamic\ Provisioning}(\mathit{basis\ period})_{bf}$ are the same dynamic provisioning variable(s) as in Equation (1). The $\mathit{controls}_{bf}$ similarly include other bank and bank-firm relationship characteristics, and ε_{bf} is the error term.

The impact periods are: (1) 2002:M2 (i.e., the start of the application sample period) to 2002:M12; (2) 2005:M7 to 2006:M12; and (3) 2008:M10 to 2010:M12, respectively. The basis periods (when the bank dynamic provisioning variables are calculated) are as before. Standard errors will be clustered at the bank level.

IV. RESULTS

1. In Good Times: Introduction of Dynamic Provisioning

a. The Independent Variable Dynamic Provision

The summary statistics in Table 2 show that following the introduction and enforcement of dynamic provisioning in 2000:Q3 there is ample variation in the dynamic provisions (over total assets) that banks have to make. The mean of the banks' *Dynamic Provision* (based on their loan portfolio in 1998:Q4 to avoid self-selection issues) is 0.26 percent, its median 0.22, and a standard deviation 0.10, ranging from a maximum of 0.86 to a minimum value of 0 percent (i.e., some banks had very high current specific provisions so they did not immediately have to additionally provision; on the other hand, banks that had to provision more did not decrease Tier-1 capital).

Not reported is how *Dynamic Provision* varies across banks' characteristics. Banks with a lower liquidity ratio were facing higher dynamic provisioning, and so were commercial banks (more than savings banks and cooperatives). Banks that were lending more to small, levered, profitable, young or with more tangible assets firms also provisioned more. As the policy shock was not randomized across banks controlling for bank and firm characteristics, or saturating specifications with firm or firm * bank type fixed effects is therefore crucial to identify its effect on credit availability.

b. Loan-Level Results

In Table 3 we display the estimates from loan level specifications with our main dependent variable, i.e., *Δlog Commitment*, and also with *Δlog Drawn* and *Loan Dropped?*, that together capture credit availability on the intensive and extensive margin for existing credit relationships, and with three dependent variables that capture loan terms (i.e., *ΔLong-Term Maturity Rate (>1 year)*, *ΔCollateralization Rate*, and *ΔDrawn to Committed Ratio*). We refer to their summary statistics (that are also in Table 2) as we discuss our estimates.

In Models 1 to 8 in Table 3 we regress our main dependent variable *Δlog Commitment* from 2000:Q1 to 2001:Q2 on *Dynamic Provision* and pertinent combinations of the following sets of characteristics and fixed effects: Other Bank,

Bank-Firm Relationship, and Loan *Characteristics*, and the following sets of *Fixed Effects*: Province and Industry, Firm, or Firm * Bank Type fixed effects. The estimations are done for samples that include *all* observations or observations from bank-firm pairs with *Multiple Bank-Firm Relationships Only* and/or with *Firm Characteristics Only*. Standard errors are clustered at the bank level, but in unreported estimations we check the robustness of our most salient findings to multiple clustering at the bank and firm level. All results hold under multi-clustering.

Given the empirical strategy we follow, we start with a minimum set of bank and bank-firm relationship characteristics as well as province and industry fixed effects in the specifications. Though Model 1 starts with 666,698 observations, the sample criteria ultimately determine the number of observations that is used in each regression, i.e., 313,234 observations in Model 2 for the sample with firm characteristics and 416,611 observations in Model 3 for the sample with multiple bank-firm relationships for example. The coefficient on *Dynamic Provision* is negative and statistically significant in all three models.

Next, we introduce firm fixed effects. The estimated coefficient on *Dynamic Provision* using firm fixed effects (in Model 4) is statistically speaking not different from the estimate when only observable characteristics are included (in Model 3). As explained before this implies that firm-level regressions controlling only for observables can identify the aggregate firm-level results of credit availability. Adding loan characteristics (in Model 5) also leaves the coefficient estimate mostly unaffected.

The coefficient on *Dynamic Provision* is also economically relevant. In Model 6 for example, our benchmark model that is saturated with firm fixed effects in addition to bank and bank-firm characteristics and estimated for all multiple-relationship observations for which firm characteristics are also available, the estimated coefficient equals -0.389***.[13] This estimate implies that a one standard deviation increase in *Dynamic Provision* (i.e., 0.10 percent) cuts committed lending by 4

[13] *** Significant at 1 percent, ** significant at 5 percent, and * significant at 10 percent. For convenience we will also indicate – in addition to the estimated standard errors in parentheses – the significance levels of the estimates that are mentioned further in the text.

percentage points. That is a sizable effect,[14] as loan level committed lending contracted by 2 percent on average from 2000:Q1 to 2001:Q2.

In Figure 3 we display with a black line the estimated coefficients on *Dynamic Provision* for Model 6 when altering the time period over which *Δlog Commitment* is calculated, i.e., from 2000:Q1 to the quarter displayed on the horizontal axis (starting in 1999:Q2). The dashed black lines indicate a two standard errors confidence interval. The estimated coefficients are statistically significant in 2000:Q2 when dynamic provisioning was formally introduced and turn also economically more relevant in 2000:Q3, our policy experiment date, when dynamic provisioning started to be enforced (this lack of any significant pre-shock trend in dynamic provisioning is consistent with the simple plots of the provisioning in the Appendix, indicating that banks made additional provisions only after the introduction by law of the new requirements).

In sum, banks with higher dynamic provisions to be put in place after the introduction of dynamic provisioning cut their total credit commitment to the same firm more after the policy shock (as compared to before the shock) than banks with lower dynamic provisioning requirements.

Results remain virtually unaffected if we load in firm * bank type fixed affects (in Model 7); or add to our parsimonious set of crucial *Bank Characteristics* (which comprises *Ln(Total Assets)*, *Capital Ratio*, *Liquidity Ratio*, *ROA*, *Doubtful Ratio*, in addition to *Commercial Bank* and *Savings Bank* dummies) the following five additional bank characteristics that proxy for bank risk-taking: *Loans to Deposits Ratio*; *Construction, Real Estate and Mortgages over Total Assets*; *Net Interbank Position over Total Assets*; *Securitized Assets over Total Assets*; and the *Regulatory Capital Ratio*. The estimated coefficient (untabulated) then equals -0.305 (0.101) ***. Adding squared and cubed terms of all bank characteristics (in total 32 terms) leaves

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[14] For a bank with 100 Euros in loans financed with 94 in deposits and 6 in equity capital for example (in Table 2 the sample mean capital ratio equals 6.01 percent), book equity drops to 5.90 after a dynamic provision of 0.10 is imposed. If book equity has to equal 6 percent, and no new equity is raised, lending has to shrink by 1.67 percent to 98.33 (= 5.90/0.06). Notice however that our estimates are based on bank – firm level observations that are not weighted by the amount of credit. Hence, if credit is cut especially by those banks that lend only small amounts to the firm, then the bank – firm level regressions may be magnifying the estimated average elasticity. Indeed, if we weigh each observation by the amount of credit, we find no average impact, implying that credit is proportionally cut more by those banks that currently lend only small amounts to the firm. In the next section we find that growth in firm-level credit (which incorporates borrowing after the introduction from "new", i.e., non-current, banks as well) is similarly not affected.

the estimate again mostly unaffected, i.e., -0.328 (0.145) **. Both robustness checks will also be done for the corresponding benchmark models that we present later, but given their very limited impact (also then) these will not be mentioned further.

To allay any remaining endogeneity concerns we further exclude savings banks or the very large banks (that potentially dominate the policymakers' minds when drawing up their plans for dynamic provisioning), and the estimated coefficient on the dynamic provision variable then equals -0.495 (0.096) *** and -0.437 (0.107) ***, respectively.

Moreover, in Model 8 we replace *Dynamic Provision (1998:Q4)* with the change in the *Dynamic Provision Funds* from 2000:Q1 to 2001:Q2, which is the level of provisioning actually chosen by the bank during the impact period, instrumented with the until-now-employed and formula-determined *Dynamic Provision (1998:Q4)*. The estimated coefficient in the first stage equals 0.691 (0.188) *** (i.e., the instrument does not suffer from a weak-instrument problem), while the estimated coefficient (from the second stage and tabulated in Model 8) equals -0.575 (0.169) ***, which implies an almost identical economic relevancy (taking into account the different standard deviations of the two variables of dynamic provisioning).

Estimates in Models 9 to 14 in Table 3 show that after the introduction of dynamic provisioning banks not only tightened credit commitments, but consistently also credit drawn (though credit drawn is potentially more firm demand related than credit committed) and loan continuation, loan maturity, collateralization, and credit drawn over committed (which reflects changes in cost of credit given that firms with at least two credit lines will draw more after the shock from banks with cheaper credit), though not all estimates are always statistically significant.[15] Hence banks overall tighten credit conditions following the introduction of dynamic provisioning which in effect meant a strengthening in bank capital requirements.

Next we investigate whether the tightening differs across bank and firm characteristics. Table 4 tabulates the benchmark specifications that also include interactions of dynamic provision with: (a) *Bank* total assets, capital ratio, ROA, and non-performing loan ratio; (b) *firm* total assets, capital ratio, ROA, and bad credit

[15] The estimated coefficients on *Dynamic Provision* in Models 10 and 11 in Table 3 for example are not statistically significant, but are statistically significant for an impact period extending past 2001:Q3 (not reported). This time lag in reaction is likely occurring because as long as all loans (including those with a longer maturity) are not fully repaid, the dependent variable *Loan Dropped?* remains equal to zero.

history; and (c) the length of the *bank-firm* relationship. The estimates in Table 4 indicate that dynamic provisioning cuts committed credit more at smaller banks and for smaller firms. Interestingly, lowly-capitalized firms are less affected by credit supply restrictions from more affected banks, maybe because banks with higher dynamic provision requirements take on higher risk to compensate for the increase in the cost of capital (and hence the lowering of bank profits).

In Model 6 in Table 4 we add bank fixed effects. The estimated coefficients on the interactions of dynamic provision with the firm characteristics are virtually unaffected, suggesting once more that unobserved bank heterogeneity is unlikely to account for the variation in committed lending observed following the policy experiment.

c. *Firm- and Loan Application-Level Results*

Loan-level results imply that the increase in countercyclical capital buffers tighten the supply of bank credit. However, at the firm level effects could be mitigated if firms can obtain credit from the less affected banks. Hence, to assess the aggregate macroeconomic relevance of the introduction of dynamic provisioning we now turn to firm-level estimations.

Back to Table 3, in Models 15 to 19 we consecutively regress our main dependent credit variable at the firm level, i.e., *Δlog Commitment (2000:Q1-2001:Q2)*, in addition to *Δlog Drawn (2000:Q1-2001:Q2)*, and firm *Δlog Total Assets (1999:Q4-2001:Q4)*, *Δlog Employees (1999:Q4-2001:Q4)*, and *Firm Death? (2001)* on *Dynamic Provision (1998:Q4)*$_b$ and pertinent combinations of bank, relationship, firm and loan characteristics, and province and industry fixed effects (as the analysis is at the firm level, firm fixed effects cannot be included).

For the specifications explaining our main credit variable, i.e., credit commitment, in Models 15 and 16 in Table 3 the estimated coefficients on *Dynamic Provision* are statistically insignificant. The blue lines in Figure 3 show that after two quarters the estimated coefficient equals a marginally significant -0.1 *, implying that a one standard deviation increase in *Dynamic Provision* (i.e., 0.10 percent) cuts committed lending only by 1 percentage point at the firm level (one quarter the size of the effect at the loan level). However, three quarters after the introduction of dynamic provisioning, the estimated coefficients lose both statistical and economic significance, suggesting that in good times firms can swiftly turn to different banks outside the set of current banks that were employed prior to the introduction (and that are potentially less affected by the introduction of dynamic provisioning) or even sufficiently shift borrowing within this set of current banks to less affected ones. Consistent with this view, we find no real effects on firm total assets, employment, or survival in Models 17 to 19 in Table 3.

We also analyze the extensive margin of new lending. We find no impact in Model 20 on the probability that loan applications from firms, that are currently not borrowing from the banks they apply to, are accepted and granted, suggesting that the firms' ability to substitute borrowing to non-current banks is unaffected by the introduction of dynamic provisioning. It is important to notice that there is no data on loan applications before 2002.

In sum, our estimates show that the introduction of dynamic provisioning in good times modified the behavior of banks, yet only in the short run significantly affected credit to firms without having any long substantial negative implications for their financing or performance. The estimates therefore suggest that dynamic provisioning introduced at the right time can be a potent countercyclical tool that changes banks' behavior, yet that is fairly benign for firms.

2. *In Good Times: Modification of Dynamic Provisioning*

a. *The Independent Variable: Dynamic Provision*

For the policy experiment in 2005:Q1 we instrument the change in dynamic provision funds between 2004:Q4 and 2005:Q2 with the dynamic provision funds in 2004:Q4 over the percent latent loss in the loan portfolio which is the relevant policy parameter value α set by the *Banco de España* (as is explained in the Appendix) times the stock of loans at the end of 2004:Q4 (labeled *Loans* in the Appendix), scaled by total assets. This latter variable captures the situation of the dynamic provision funds with respect to its limit as is explained in the Appendix. We also include predetermined bank characteristics.

Consequently the specification we run in the first stage equals:

$$\log \frac{Dynamic\ Provision\ Funds(2005{:}\,Q2)_b}{Dynamic\ Provision\ Funds(2004{:}\,Q4)_b} = constant + \rho \frac{Dynamic\ Provision\ Funds(2004{:}\,Q4)_b}{Latent\ Risk(2004{:}\,Q4)_b} + Bank\ Characteristics_b + \varepsilon_b \quad (4)$$

where *Dynamic Provision Funds* is the (in all cases positive) stock of provisions, scaled by total assets. *Latent Risk* is an estimate of the percent latent loss in the loan portfolio, which is the parameter α times the stock of loans at the end of 2004:Q4, scaled by total assets.

The rationale for this approach is that the dynamic provisioning parameters were increased, but at the same time the ceiling of the dynamic provision funds was lowered. For banks well below the ceiling the increase in parameters meant more provisioning. But for the majority of banks that were at or close to the ceiling, the modification implied a "forced" net negative provisioning. The instrument which is (inversely) proportional to the bank's "distance to the ceiling" directly captures how the policy experiment will affect the provisioning requirements for the bank. We consequently expect a negative relationship between the change in dynamic provisions and the level of dynamic provision funds at the end of 2004. And indeed, the estimated coefficient $\hat{\rho}$ equals -0.350 (0.056) *** (using 173 bank observations and with robust standard errors).

The summary statistics in Table A.1 (the tables and figure for this experiment are in Appendix) show that also following the modification of dynamic provisioning requirements there is ample variation in the dynamic provisions (over total assets) that banks made as a consequence over the period 2004:Q4 to 2005:Q2. The mean of the *Dynamic Provision* (which is the mean of the bank-specific projection from Equation (4) at the loan level) equals 0.05 percent, its median equals 0.00, with a standard deviation 0.14, and values ranging from a maximum of 0.86 to a minimum value of -0.18 percent. In contrast, both the flow of provisions measured at the bank level and the stock of provisions as a percentage of total loans actually dropped, plainly reflecting the lowering of the ceiling that took place.

b. Results

In Table A.2 we display the estimates from loan- and firm-level specifications with a line-up of dependent variables similar to Table 3 that capture firm-bank level credit availability on the intensive and extensive margin, loan terms, and firm-level credit availability and performance. In Figure A.1 we display the estimated coefficients on *Dynamic Provision* when altering the time period over which the logarithm of committed credit is calculated, i.e., from 2004:Q4 to the quarter displayed on the horizontal axis, while Table A.3 tabulates representative specifications that include interactions of *Dynamic Provision* with relevant bank and firm characteristics.

The estimated coefficients on *Dynamic Provision* in Table A.2 are equal in sign but smaller in absolute and economic magnitude than those in Table 3. Take our benchmark Model 6, a model that is saturated with firm fixed effects in addition to bank, bank-firm and firm characteristics and is estimated for multiple relationship observations only. The estimated coefficient on *Dynamic Provision* in this model equals -0.115**. This estimate implies that a one standard deviation increase in *Dynamic Provision* (i.e., 0.14 percent) cuts committed lending by 2 percentage points. Though half the estimated effect in Table 3, this is still a fairly sizable effect as committed lending expanded only by 1 percent on average from 2004:Q4 to 2006:Q2.

The estimates of the coefficient on *Dynamic Provision* in specifications with the other loan credit availability and loan terms as dependent variables are either the same in sign but smaller in absolute size than for the first policy experiment, or statistically insignificant (Models 8 to 13). The same holds for the coefficient estimates in the firm-level specifications (Models 14 to 18), for the estimates rolling over time (Figure A.1), for the estimates of the interactions with bank or firm characteristics (Table A.3), and for the estimates in the loan application-level specifications (Model 19), of which none are statistically significant.

In sum, the modification of dynamic provisioning had an impact that was directionally similar but somewhat more muted than the introduction of dynamic provisioning. Likely this is reflecting the fact that the modification only marginally affected dynamic provisioning requirements during good (boom) times, such that its impact was easily mitigated by either banks and/or firms.

3. *In Bad Times: Floor Lowering and Dynamic Provision Funds into the Crisis*

a. *The Independent Variables*

Finally, we now turn to the analysis of the impact of dynamic provisioning on lending and firm performance in bad times when both a policy experiment took place and the countercyclical nature of dynamic provisioning were highlighted by the unexpected crisis shock, as the dynamic (general) provision flow turns negative (and the stock correspondingly starts to decline) in 2008 (see Appendix), due to the decrease in provisioning requirements.

The lowering in 2008:Q4 of the floor of provision funds which affected mostly the banks with the lowest provision funds in the preceding quarter is captured by the dummy variable *d(<25% Dynamic Provision Funds)*, a variable that equals one if the bank is in the lowest quartile in 2008:Q3, and equals zero otherwise. 42 percent of the 1,101,806 loans are made by banks in this lowest of fund quartiles (Table 5).

For the concurrent crisis shock we calculate how much each bank had built up as dynamic (general) provision funds (over assets) just prior to the onset of the crisis in Spain. The variable *Dynamic Provision Funds* in 2007:Q4 varies across banks, with a mean of 1.17, a median of 1.14, a standard deviation that equals 0.23, and ranging between 0.06 and 2.57. Not tabulated is our analysis that shows that banks with relatively more funds have only marginally lower capital and liquidity ratios, but lend more to smaller, less capitalized, more profitable and more recently engaged firms. Controlling for bank and firm characteristics is again crucial to help identify credit.

b. *Loan-Level Results*

As before, the specifications in Table 6 at the loan, firm, or loan application level for the various dependent credit and performance variables feature the pertinent combinations of characteristics and fixed effects, are estimated for the various samples (that include all or multiple relationship observations only, and/or all or observations with firm characteristics only), and with standard errors clustered at the bank or main bank level (and robust to multi-clustering at the bank and firm level, checks which are left unreported).

For example in Models 1 to 7 in Table 6 we regress *Δlog Commitment* from 2008:Q1 to 2009:Q4 on *d(<25% Dynamic Provision Funds)*, *Dynamic Provision Funds*, and the indicated sets of characteristics and fixed effects. The estimated coefficients on both dynamic provisioning variables are positive and statistically significant. Both are also economically relevant.

Take again the benchmark Model 6 saturated with firm fixed effects in addition to bank and bank-firm characteristics, and estimated for the multiple relationship and firm characteristics only sample. The estimated coefficient on *d(<25% Dynamic Provision Funds)* equals 0.096 (0.030) ***, implying that committed lending at banks in the lowest quartile in terms of dynamic provision funds (and were therefore positively affected by the lowering of the funds floor value) grew by 10 percentage points more between 2008:Q1 and 2009:Q4 than at banks in other quartiles. This is a sizeable difference and therefore the policy action likely mitigated an even more precipitous drop in committed lending, even though its mean is still -25 percent.

The estimated coefficient on *Dynamic Provision Funds* in Model 6 equals 0.201 (0.069) ***, which implies that one standard deviation more in terms of funds (i.e., 0.23) delivers 5 percentage points more growth in committed lending between 2008:Q1 and 2009:Q4, and that at a bank with a mean level of funds (i.e., 1.17 percent) committed lending grew by almost 25 percentage points more than at a bank with zero funds. These estimates vividly illustrate the countercyclical potency of dynamic provisioning.

Figures 4 and 5 again display the estimated coefficients (and two standard deviations intervals) for Model 6 for horizons for committed lending that start in 2008:Q1 and are rolled forward between this starting date and 2010:Q4. The graphs show that the estimates not even reach their maxima for the period between 2008:Q1 and 2009:Q4 that was tabulated in Table 6, and are permanently positive during the crisis and statistically significant over all horizons after the start of the crisis (though not surprisingly the effect of the policy shock diminishes during 2010).

Returning to Table 6, results are very similar when loading in firm * bank type fixed effects (Model 7), excluding either the savings banks or the very large banks (untabulated), and crucially when instrumenting the actual Dynamic Provision Funds in 2007:Q4 with the simulated Dynamic Provision Funds in 2007:Q4 fixing the bank loan portfolio in 2000:Q3, that is 7 years prior to the shock (Model 8) and assuming no bank-specific provisioning takes place. The instrumentation is especially important in the case of this variable (as compared to the three policy shocks) as banks could have dynamically provisioned more than required by regulation. By instrumenting with the part explained by the regulation (the formula) applied to the portfolio in 2000:Q3 (i.e., the moment of introduction of dynamic provisions) we remove the potentially endogenous part in 2007:Q4. The estimated coefficient in the first stage equals 0.772 (0.133) ***, and the instrument does not suffer from a weak-instrument problem.

Results are further unaffected for the alternative intensive margin of drawn credit (Model 9) and for the extensive margin of no more lending (Models 10 and 11). The estimated coefficients in Model 10, i.e., -0.046 (0.014) *** and -0.054 (0.030) * for example, imply that: (a) Credit was discontinued in 5 percentage points fewer cases at banks in the lowest quartile in terms of dynamic provision funds than at banks in other quartiles (30 percent of lending was discontinued in 2008:Q1-2009:Q4), hence banks in the lowest quartile benefited from the policy shock; and that (b) banks with mean funds were 6 percentage points less likely to discontinue lending to a firm than banks with zero funds. This effect is again permanent, especially for the policy experiment (not reported).

Banks in the lowest quartile that benefited most from the floor lowering and banks with more dynamic provision funds prior to the crisis not only ease credit volume more than other banks, but also somewhat its cost (in Model 14 the estimated coefficients equal 0.028 (0.007) *** and 0.013 (0.015), respectively, implying that firms decide to draw relatively more on these likely lower-cost credit lines). But interestingly these same banks also shorten loan maturity – in Model 12: -0.074 (0.021) *** and -0.175 (0.047) *** – and increase collateral requirements – in Model 13: 0.012 (0.004) *** and 0.031 (0.010) *** – in both a statistically significant and economically relevant manner which for maturity is also permanent (not reported). These banks possibly tighten conditions to compensate for the higher risk they take lending more during the crisis.

c. *Firm- and Loan Application-Level Results*

The firm-level estimates in Models 15 to 19 in Table 6 (and Figures 4 and 5) suggest firms cannot substitute for the impact we document at the loan level. In Model 15 for example the estimated coefficients equal 0.058 (0.015) *** and 0.105 (0.036) ***, respectively, implying that for firms borrowing committed from banks in the lowest fund quartile is 6 percentage points higher than when borrowing from other banks, and 2 (11) percentage points higher when its bank has one standard deviation (one percentage point) more in funds,[16] partly offsetting the steep contraction in committed borrowing by 27 percent for the mean firm. Figures 4 and 5 (the blue lines) show this effect is permanently large and statistically significant.

Given that we control for bank and firm observable characteristics and given that in the loan-level regressions the two coefficients in the models with firm fixed effects and the models with observables are not statistically different, the firm-level results can be interpreted as being driven by credit supply shocks.

Total asset growth of firms at beneficially affected and well-funded banks is also higher during the 2007:Q4 to 2009:Q4 period. The estimates in Model 17 of 0.007 (0.004) ** 0.025 (0.011) ** imply a 1 percentage point higher growth for firms engaged with banks in the lowest quartile or with one standard deviation more in funds (mean growth was -2 percent). The effects for employment growth and firm death are consistent in sign when statistically significant (Models 18 and 19) – e.g., a 1 percentage point higher ratio of general provisions imply a 2.7 percentage point higher employment growth rate and a 1 percentage point higher likelihood of survival – while there is no differential effect on the borrowing cost for the firms. These results suggest that the substitution of banks is more difficult in bad times than in good times. Supporting this view, we find that the granting of loan applications to non-current borrowers in bad times is substantially lower than in good times (a reduction of almost 30 percent, the summary statistics on loan application granting in Table 5 versus 2 and A.1 suggest).

Finally, the estimates in Model 20 in Table 6 provide further insight into which non-current banks in bad times firms can successfully apply to. The estimated coefficients equal -0.056 (0.015) *** and 0.094 (0.042) **, respectively, and imply that the probability a loan application is accepted and granted by a non-current bank in the lowest fund quartile is 6 percentage points lower than by other banks, and 2 percentage points higher by an approached bank with one standard deviation more in funds (i.e., semi-elasticities equal -20 and 8 percent for the mean firm). Hence, especially the well-funded banks will lend to non-current firms that seek to borrow

[16] In the extant literature a one percentage point increase in the capital ratio corresponds to a 0 to 3 percentage points increase in bank-level credit growth. In contrast to these studies our estimates pertain to the impact of the built-up (for countercyclical purposes) dynamic provision funds on firm credit growth during a deep financial crisis (the bank-level estimate in Carlson, Hui and Warusawitharana (2011) for example triples in size during the crisis years; see also Gambacorta and Marques-Ibanez (2011) and Cornett, McNutt, Strahan and Tehranian (2011)).

from them and, consequently, these banks support credit availability on both the intensive and extensive margins of lending.

Instead, the banks that were in the lowest quartile (in terms of dynamic provision funds) and that benefitted from the floor lowering are less likely to grant loans to non-current borrowers, but are more likely (the earlier estimates suggest) to route the extra credit they grant to their current borrowers (that represent the bulk of the firms in the sample but for which we do not observe loan applications).

In Table 7 we turn to further studying the effects across bank and firm characteristics. The estimates of the interaction coefficients suggest that the policy experiment was especially beneficial for lowest quartile banks with a low non-performing loan ratio and for small firms with a low capital ratio. The last result is an indication that reducing capital requirements to the lowest capitalized banks may make risk-taking more attractive, not inconsistent with strategies of gambling-for-resurrection for example.

The crisis shock similarly was absorbed best by well-funded banks with a low non-performing loan ratio and by firms with a good credit history and that had been with a bank for a longer time. So not only the volume but also the allocation of credit by well-funded banks withstood the crisis shock better. Therefore, the effects are not the same when the regulator increases capital requirements in good times to have higher buffers for when a crisis hits, than just when the regulator simply reduces the capital requirements in bad times (at least this is the case for the lowly capitalized banks).

As noted the relevance of dynamic provision funds during the crisis was strongest for banks with low non-performing loan ratios. We think that having in place more dynamic provision funds, i.e., more Tier-2 capital, directly affects credit as in bad times banks have to specifically provision for loans at a time their profits are low and external financing is costly. With higher dynamic provision funds accumulated before the crisis, banks need to increase less these provisions and hence can support more credit. But more dynamic provision funds and hence capital also indirectly lowers the cost of wholesale liquidity, which on the margin may be crucial to sustain lending during the crisis, especially for banks with low non-performing loan ratios. Put differently, banks with high non-performing loan ratios may face a capital requirement in the market that is higher and hence more binding than the regulatory requirement. A loosening of the regulatory requirement may therefore have a more muted effect on credit supply.

In sum, the estimates coming from three policy experiments and a crisis shock suggest that dynamic provisioning affect bank behavior and in effect generates countercyclical capital buffers, mitigates credit supply cycles and, therefore, has positive aggregate firm-level credit and real effects. Firms are more severely affected in bad times when switching from banks with low to high capital buffers may be difficult. Therefore, mitigating credit supply cycles may yield strong positive real effects.

V. CONCLUSIONS

A crucial issue for macropru policy is to avoid the negative externalities that may flow from the financial system to the real economy, both in good times when risk stemming from "excessive" lending nests itself into the balance sheets of banks, as well as in bad times when distressed banks contract the supply of credit to firms with good investment opportunities. A macropru solution proposed by policymakers and academic theory alike is countercyclical bank capital buffers.

We study the effects of dynamic provisioning which generates countercyclical bank capital buffers on the supply of credit to firms and the resultant real effects. Spain in the period between 1999 and 2010 offers an excellent setting to empirically identify these effects, given the three policy experiments with dynamic provisioning that took place, the unexpected crisis shock, and the comprehensive bank-, firm-, loan-, and loan application-level data that is available during this time period.

The results, overall, are consistent with the idea that dynamic provisioning generates countercyclical bank capital buffers, mitigates bank procyclicality in credit supply, and in turn generates net positive real effects at the firm-level. The buffers contract credit availability (volume and cost) in good times, but expand it in bad times. During the recent crisis at a bank with a mean level of provision funds, committed credit grew by 19 percentage points more than at a bank with zero funds for example, vividly demonstrating the countercyclical potency of dynamic provisioning!

While the effect on credit granted by a specific bank to a specific firm is always economically strong, dynamic provisioning did little to stop the credit boom to firms in good times as firms switched to less affected banks. Yet, the bank buffers build up in good times helped mitigate the credit crunch in bad times, when switching banks turned problematic (witness the decrease in the percentage in loan application granting). Concurrent with the credit contraction, we document its impact on real corporate performance, i.e., growth in firm assets and employment, and firm survival.

Consequently, our findings hold important implications for macropru policy. Our estimates unequivocally suggest that bank procyclicality can be mitigated with countercyclical capital buffers. Buffering reduces credit supply in good times (when more risk creeps into bank balance sheets) and supports bank lending in bad times with less need for costly governmental bail-outs and/or expansive monetary policy. Basel III stipulates countercyclical bank capital buffers and our findings support the reasoning that prevailed both in Basel and the G20 on these issues. Moreover, our results show that dynamic provisioning (i.e., countercyclical capital) set aggressively enough and under the right conditions can deliver the goods. The dynamic provision funds that equaled around 1.25 percent (of total loans) worked very well, but were ultimately overwhelmed by the once-in-a-lifetime crisis that hit Spain.

Our results are also important for macroeconomic modeling as we show that in bad times there are substantial real effects stemming from weak bank capital positions. Not only does aggregate bank capital matter, but as firms struggle to switch banks in bad times due to adverse selection for example (Broecker (1990); Ruckes (2004); Dell'Ariccia and Marquez (2006)), the distribution of bank capital *per se* may drive macroeconomic real effects as well. Hence, bank (capital) heterogeneity matters for macroeconomics. Finally, our results inform the recent and contentious debate among bankers, academics and policy makers on the cost of bank capital and the possible impact of raising capital requirements on the supply of bank credit to the corporate sector (Admati, DeMarzo, Hellwig and Pleiderer (2010); Hanson, Kashyap and Stein (2011)).

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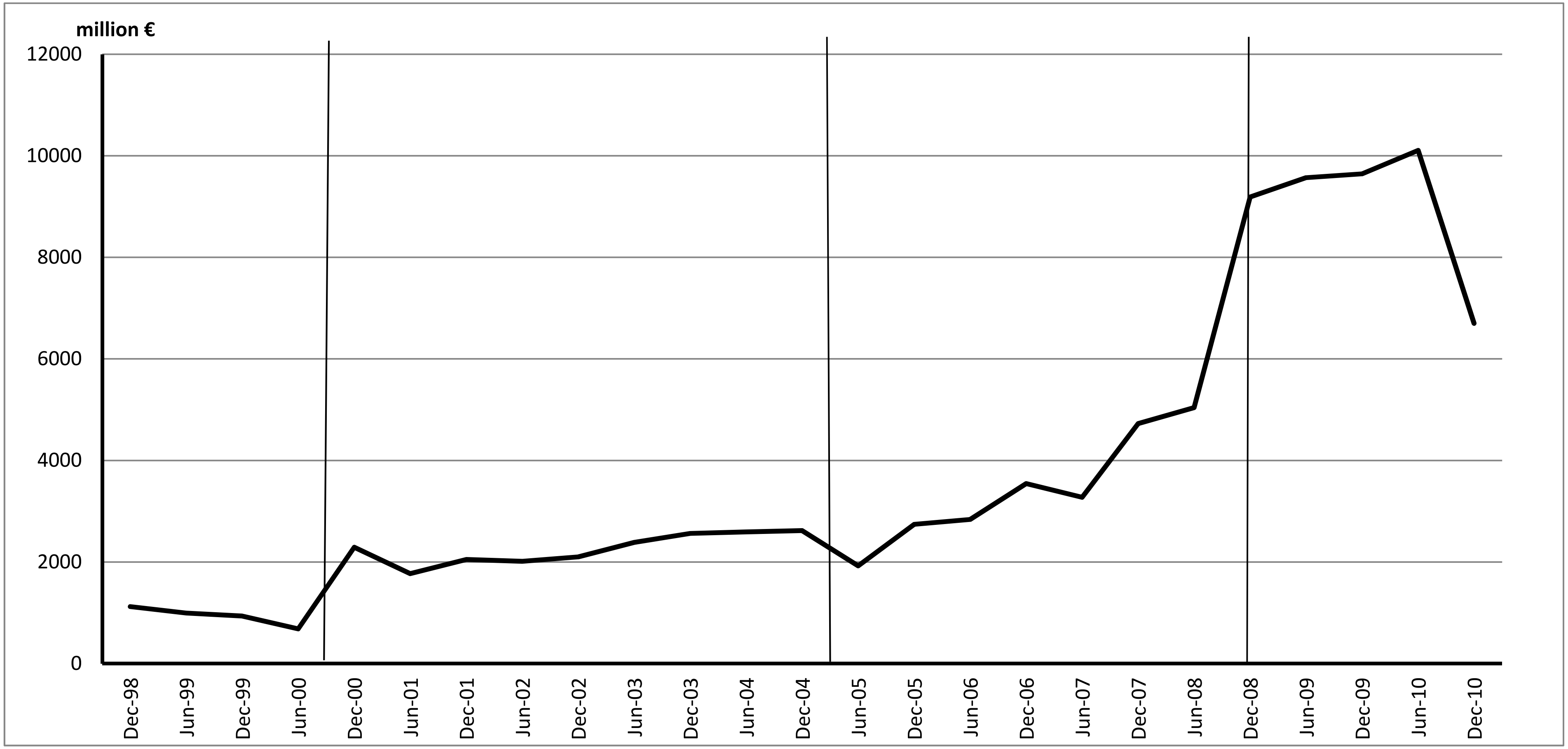
FIGURE 1

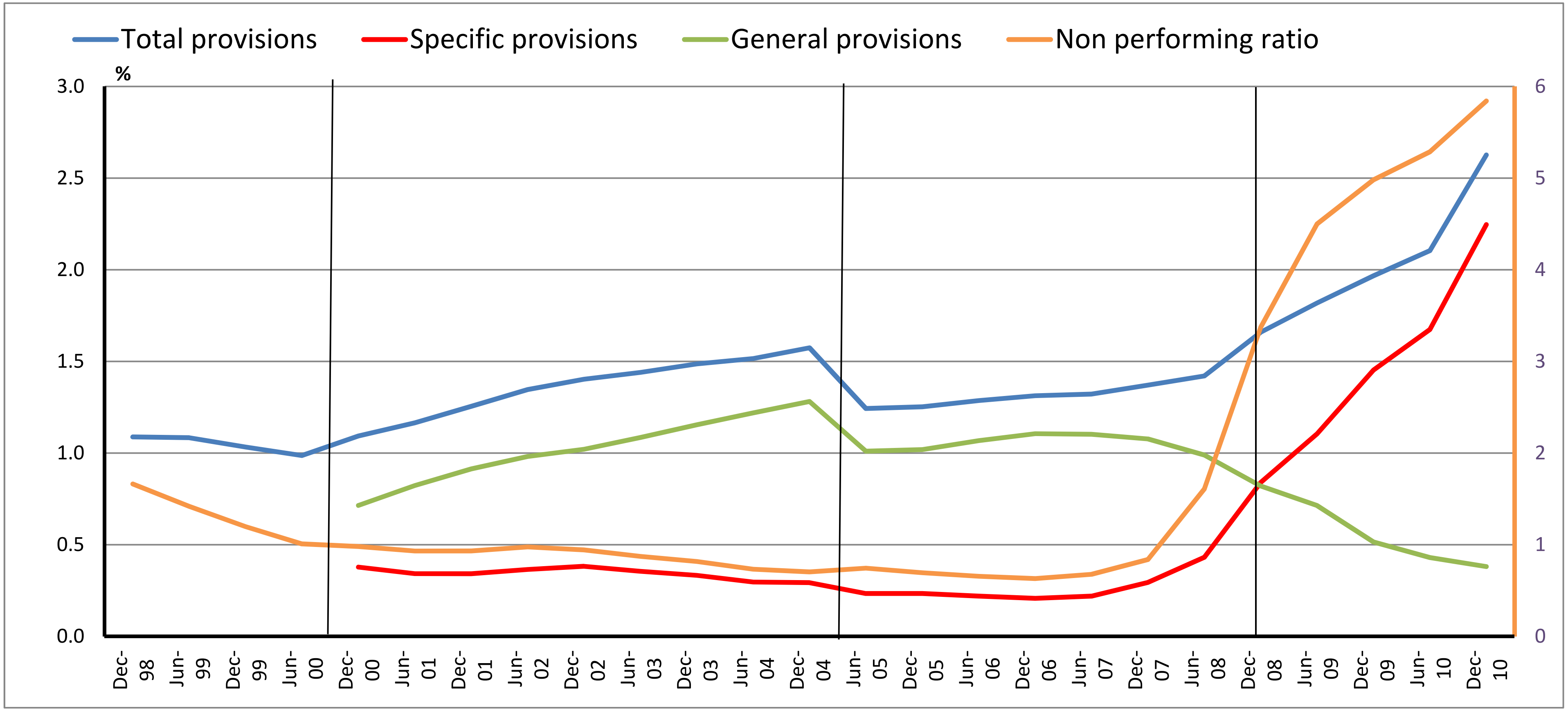
THE FLOW OF TOTAL NET LOAN LOSS PROVISIONS, IN EUROS



NOTE. -- The figure displays the flow of total net loan loss provisions (in million euros) from 1998 to 2010. The vertical lines indicate the timing of the three policy experiments.

FIGURE 2

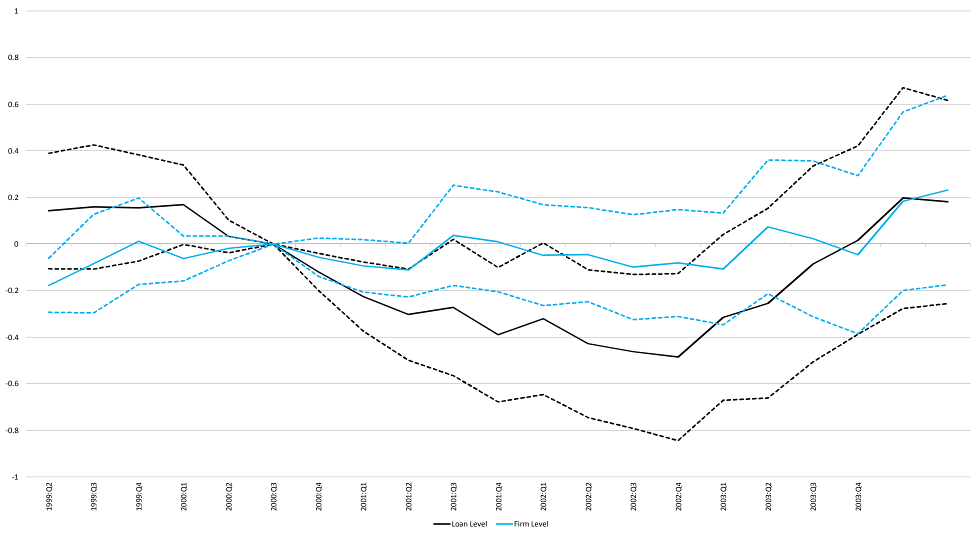
THE STOCK OF TOTAL, SPECIFIC AND GENERAL LOAN LOSS PROVISIONS, AND NON-PERFORMING LOANS, OVER TOTAL LOANS, IN PERCENT



NOTE. -- The stock of total, specific and general loan loss provision funds (left scale), and non-performing loans (right scale), as a percent of total loans granted by deposit institutions from 1998 to 2010. The vertical lines indicate the timing of the three policy experiments.

FIGURE 3

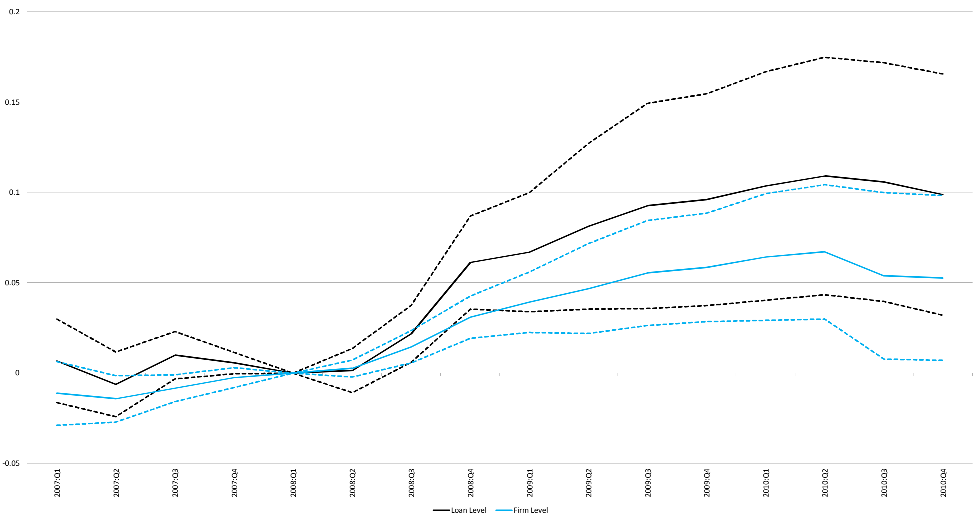
ESTIMATES OF TIME-VARYING COEFFICIENT ON THE INDEPENDENT VARIABLE DYNAMIC PROVISION FOR COMMITMENT LENDING



NOTE. -- Solid lines represent the coefficients of Dynamic Provision in Models 6 and 15 in Table 3 that are estimated with rolling time windows. Dashed lines represent the two standard error confidence band drawn around the coefficient estimates. Black lines are at the loan level, blue lines are at the firm level. Table 1 contains all variable definitions.

FIGURE 4

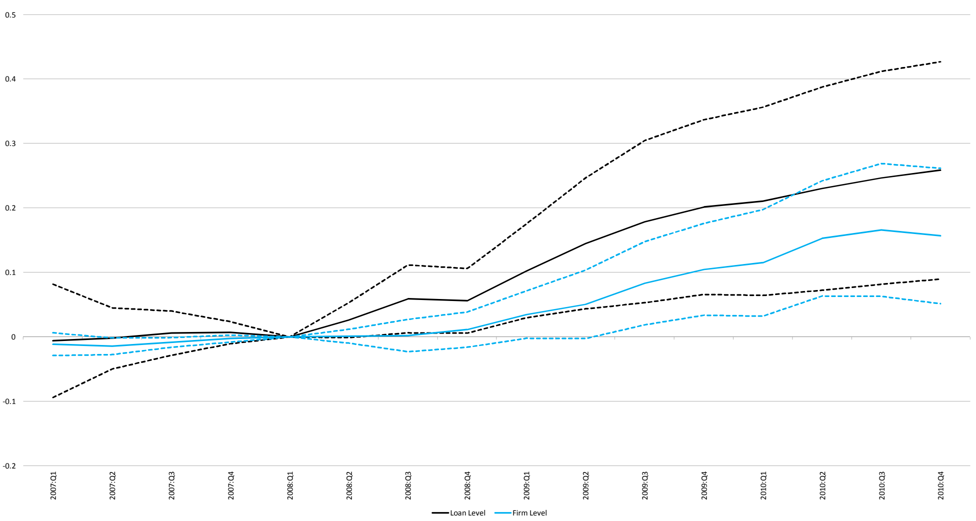
ESTIMATES OF TIME-VARYING COEFFICIENT ON THE INDEPENDENT VARIABLE d(<25% DYNAMIC PROVISION FUNDS) THAT CAPTURES THE FLOOR REMOVAL FOR COMMITMENT LENDING



NOTE. -- Solid lines represent the coefficients of d(<25% Dynamic Provision Funds) in Models 6 and 15 in Table 6 that are estimated with rolling time windows. Dashed lines represent the two standard error confidence band drawn around the coefficient estimates. Black lines are at the loan level, blue lines are at the firm level. Table 1 contains all variable definitions.

FIGURE 5

ESTIMATES OF TIME-VARYING COEFFICIENT ON THE INDEPENDENT VARIABLE DYNAMIC PROVISION FUNDS IN 2007:Q4 FOR COMMITMENT LENDING



NOTE. -- Solid lines represent the coefficients of Dynamic Provision Funds in Models 6 and 15 in Table 6 that are estimated with rolling time windows. Dashed lines represent the two standard error confidence band drawn around the coefficient estimates. Black lines are at the loan level, blue lines are at the firm level. Table 1 contains all variable definitions.

TABLE 1

DEFINITIONS OF ALL DEPENDENT AND INDEPENDENT VARIABLES USED IN THE LOAN AND FIRM LEVEL ANALYSES

Level of Analysis, *Variable Type* and Variable Name	Definition
Loan Level	
Dependent Variables (bank - firm - period)	
Δlog Commitment	Change in the logarithm of committed credit granted by bank b to firm i during period (t, s)
Δlog Drawn	Change in the logarithm of drawn credit granted by bank b to firm i during period (t, s)
Loan Dropped?	=1 if credit granted by bank b to firm i is ended during period (t, s), =0 otherwise
ΔLong-Term Maturity Rate (>1 year)	Change in the % of loan volume of maturity higher than one year by bank b to firm i during period (t, s)
ΔCollateralization Rate	Change in the % of collateralized loans by granted bank b to firm i during period (t, s)
ΔDrawn to Committed Ratio	Change in the drawn to committed credit granted by bank b to firm i during period (t, s)
Bank Dynamic Provisioning (bank)	
Dynamic Provision (1998:Q4)	Dynamic provision flows based on the new formula and applied to the loan portfolio of 1998:Q4 over total assets
Dynamic Provision (2004:Q4-2005:Q2)	Log of the dynamic provision fund of 2005:Q2 minus 2004:Q4
Dynamic Provision Funds / Latent Risk (2004:Q4-2005:Q2)	Dynamic provision fund over latent losses in 2004:Q4 used in the first stage regression
d(<25% Dynamic Provision Funds)(2008:Q3)	=1 if the dynamic provision fund over total assets is in the lower quartile, =0 otherwise
Dynamic Provision Funds (2006:Q4)	Dynamic provision fund over total assets
Other Bank Characteristics (bank)	
Ln(Total Assets)	The logarithm of total assets of bank b at time t-1
Capital Ratio	The ratio of bank equity and retained earnings over total assets of bank b at time t-1
Liquidity Ratio	The ratio of current assets held by bank b over the total assets at time t-1
ROA	The ratio of total net income over total assets of bank b at time t-1
Doubtful Ratio	The ratio of non-performing loans over total assets of bank b at time t-1
Commercial Bank	=1 if bank b is a commercial bank, =0 otherwise
Savings Bank	=1 if bank b is a savings bank, =0 otherwise

Bank-Firm Relationship Characteristic (bank - firm)	
Ln(1+Number of months with the bank)	The logarithm of one plus the duration of the lending relationship between bank b and firm f at time t-1
Firm Characteristics (firm)	
Ln(Total Assets)	The total assets of firm f in time t-1
Capital Ratio	The ratio of own funds over total assets of firm f at time t-1
Liquidity Ratio	The ratio of current assets over total assets of firm f at time t-1
ROA	The ratio of the profits over total assets of firm f at time t-1
Bad Credit History	= 1 if the firm f had doubtful loans before time t, =0 otherwise
Ln(Age+1)	The log of one plus the age in years of firm f at time t-1
Tangible Assets	The ratio of tangible assets over total assets of firm f at time t-1
Loan Characteristics (bank - firm)	
Maturity <1 year	% of all bank loan volume of firm i of maturity lower than 1 year at time t-1
Maturity 1-5 years	% of all bank loan volume of firm i of maturity between 1 and 5 years at time t-1
Collateralized Loan	% of the collateralization of all bank loan volume of firm i at time t-1
Ln(Loan Amount)	The logarithm of all bank loan volume of firm i in the previous year
Firm Level	
Dependent Variables (firm)	
Δlog Commitment	Change in the logarithm of committed credit granted by all banks to firm i during period (t, s)
Δlog Drawn	Change in the logarithm of drawn credit granted by all banks to firm i during period (t, s)
Δlog Total Assets	Change in the logarithm of total assets of firm i during period (t, s)
Δlog Employees	Change in the logarithm of total employees of firm i during period (t, s)
Firm Death?	=1 if firm is liquidated during period (t, s), =0 otherwise
Loan Application Level	
Dependent Variable (bank-firm)	
Loan Application Is Accepted and Granted	=1 if the loan application is accepted and granted by bank b to firm f during period (t, s), =0 otherwise

NOTE. -- See Section 2 and the Appendix for details on the calculations of the Bank Dynamic Provisioning variables.

TABLE 2

SUMMARY STATISTICS FOR DEPENDENT AND INDEPENDENT VARIABLES USED IN THE LOAN AND FIRM LEVEL ANALYSIS OF THE INTRODUCTION OF DYNAMIC PROVISIONING IN 2000:Q3

Level of Analysis, *Variable Type* and Variable Name	Unit	Mean	Standard Deviation	Minimum	Median	Maximum
Loan Level						
Dependent Variables (bank - firm; 2000:Q1-2001:Q2)						
Δlog Commitment	-	-0.02	0.77	-2.34	-0.03	2.47
Δlog Drawn	-	-0.01	0.81	-2.30	-0.03	2.51
Loan Dropped?	0/1	0.25	0.43	0	0	1
ΔLong-Term Maturity Rate (>1 year)	-	0.00	0.32	-1.00	0.00	1.00
ΔCollateralization Rate	-	0.00	0.18	-1.00	0.00	1.00
ΔDrawn to Committed Ratio	-	-0.23	0.32	-1.00	-0.20	1.00
Bank Dynamic Provisioning (bank; 1998:Q4)						
Dynamic Provision	%	0.26	0.10	0.00	0.22	0.86
Other Bank Characteristics (bank)						
Ln(Total Assets)	Ln(000 Euros)	17.03	1.72	9.08	17.12	19.56
Capital Ratio	%	6.01	2.08	0.00	5.29	53.86
Liquidity Ratio	%	28.40	8.78	0.03	29.17	93.47
ROA	%	1.33	0.74	-16.08	1.08	4.69
Doubtful Ratio	%	1.15	0.48	0.00	1.03	3.29
Commercial Bank	0/1	0.60	0.49	0	1	1
Savings Bank	0/1	0.35	0.48	0	0	1
Bank-Firm Relationship Characteristic (bank - firm)						
Ln(1+Number of months with the bank)	Ln(1+Months)	3.52	1.26	0.00	3.76	5.21
Firm Characteristics (firm)						
Ln(Total Assets)	Ln(000 Euros)	7.37	1.58	2.20	7.16	17.12
Capital Ratio	%	23.32	17.03	0.00	19.67	97.96
Liquidity Ratio	%	5.66	7.77	0.00	2.94	100.00
ROA	%	7.32	7.32	-25.50	6.28	55.36
Bad Credit History	0/1	0.16	0.37	0	0	1
Ln(Age+1)	Ln(1+Years)	2.30	0.79	0.00	2.40	4.87
Tangible Assets	%	24.91	21.72	0.00	19.22	100.00
Loan Characteristics (bank - firm)						
Maturity <1 year	0/1	0.57	0.44	0	1	1
Maturity 1-5 years	0/1	0.27	0.39	0	0	1
Collateralized Loan	0/1	0.15	0.33	0	0	1
Ln(Loan Amount)	Ln(000 Euros)	4.00	1.95	0.00	4.20	13.46
Firm Level						
Dependent Variables (firm)	-					
Δlog Commitment (2000:Q1-2001:Q2)	-	-0.05	0.52	-2.37	-0.06	1.98
Δlog Drawn (2000:Q1-2001:Q2)	-	-0.04	0.57	-2.40	-0.06	2.20
Δlog Total Assets (1999:Q4-2001:Q4)	-	0.43	0.36	-0.61	0.39	1.82
Δlog Employees (1999:Q4-2001:Q4)	-	0.10	0.42	-1.39	0.05	1.70
Firm Death? (2001)	0/1	0.03	0.17	0	0	1
Loan Application Level						
Dependent Variable (bank-firm; 2002:M2-2002:M12)						
Loan Application Is Accepted and Granted	0/1	0.38	0.49	0	0	1

NOTE. -- Table 1 contains all variable definitions. The number observations at the loan level: 666,698; at the firm level: 76,593; at the loan application level: 15,253.

TABLE 3

LOAN AND FIRM LEVEL ANALYSIS OF THE EFFECTS OF THE INTRODUCTION OF DYNAMIC PROVISIONING IN 2000:Q3

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Level	**Loan**										
Dependent Variable	Δlog Commitment (2000:Q1-2001:Q2)	Δlog Commitment (2000:Q1-2001:Q2)	Δlog Commitment (2000:Q1-2001:Q2)	Δlog Commitment (2000:Q1-2001:Q2)	Δlog Commitment (2000:Q1-2001:Q2)	Δlog Commitment (2000:Q1-2001:Q2)	Δlog Commitment (2000:Q1-2001:Q2)	*2-Stage Least Squares* Δlog Commitment (2000:Q1-2001:Q2)	Δlog Drawn (2000:Q1-2001:Q2)	Loan Dropped?	Loan Dropped?
Dynamic Provision (1998:Q4)$_b$	-0.336 **	-0.366 **	-0.366 **	-0.357 ***	-0.259 **	-0.389 ***	-0.397 ***	*-0.575* ***	-0.451 ***	0.115	0.104
	(.164)	(.186)	(.168)	(.123)	(.12)	(.147)	(.106)	*(.169)*	(.108)	(.117)	(.123)
Other Bank Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Firm Relationship Characteristic	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Characteristics	No	No	No	No	Yes	No	No	No	No	No	Yes
Province and Industry Fixed effects	Yes	Yes	Yes	--	--	--	--	--	--	--	--
Firm Fixed Effects	No	No	No	Yes	Yes	Yes	--	--	--	Yes	Yes
Firm * Bank Type Fixed Effects	No	No	No	No	No	No	Yes	Yes	Yes	No	No
Sample with Multiple Bank-Firm Relationships Only	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample with Firm Characteristics Only	No	Yes	No	No	No	Yes	No	No	No	No	No
Cluster	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
Number of Observations	666,698	313,234	416,611	416,611	416,611	237,905	416,611	416,611	366,364	571,007	571,007

Model	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Level	**Loan**			**Firm**					**Loan Application**
Dependent Variable	ΔLong-Term Maturity Rate (>1 year) (2000:Q1-2001:Q2)	ΔCollateralization Rate (2000:Q1-2001:Q2)	ΔDrawn to Commited Ratio (2000:Q1-2001:Q2)	Δlog Commitment (2000:Q1-2001:Q2)	Δlog Commitment (2000:Q1-2001:Q2)	Δlog Total Assets (1999:Q4-2001:Q4)	Δlog Employees (1999:Q4-2001:Q4)	Firm Death? (in 2001)	Loan Application Is Accepted and Granted (2002:M2-2002:M12)
Dynamic Provision (1998:Q4)$_b$	-0.163 ***	0.082 ***	-0.030	0.010	0.014	-0.001	-0.099	0.000	0.168
	(.049)	(.03)	(.04)	(.109)	(.103)	(.002)	(.067)	(.013)	(.153)
Other Bank Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Firm Relationship Characteristic	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Characteristics	--	--	--	Yes	Yes	Yes	Yes	Yes	No
Loan Characteristics	Yes	Yes	Yes	No	Yes	No	No	No	No
Province and Industry Fixed effects	--	--	--	Yes	Yes	Yes	Yes	Yes	--
Firm Fixed Effects	Yes	Yes	Yes	><	><	><	><	><	Firm-Time
Sample with Multiple Bank-Firm Relationships Only	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Sample with Firm Characteristics Only	No	No	No	Yes	Yes	Yes	Yes	Yes	No
Cluster	Bank	Bank	Bank	Main Bank	Main Bank	Main Bank	Main Bank	Main Bank	Bank
Number of Observations	416,611	416,611	416,611	76,593	76,593	59,449	41,146	92,576	15,253

NOTE. -- Model 6 corresponds to Equation 1; the adjacent text explains Models 1 to 14. In Model 8 in the first stage we regress *Δ Dynamic Provision Funds (2000:Q1 - 2001:Q2)* on *Dynamic Provision (1998:Q4)*. The estimated coefficient equals 0.691*** (0.188). In the second stage the instrumented *Δ Dynamic Provision Funds (2000:Q1 - 2001:Q2)* replaces *Dynamic Provision (1998:Q4)*. Model 15 corresponds to Equation 2; the adjacent text explains Models 15 to 19. Model 20 corresponds to Equation 3. Table 2 contains the list of variables for each set of characteristics and Table 1 the definition of all variables. The Ln(Loan Amount) included in the Loan Characteristics is averaged from 1998:Q4 to 1999:Q4. Coefficients are listed in the first row, robust standard errors that are corrected for clustering at the indicated level are reported in the row below in parentheses, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included. "No" indicates that the set of characteristics or fixed effects is not included. "><" indicates that the set of fixed effects cannot be included (because the regression is cross-sectional at the level of the fixed effects). "--" indicates that the indicated set of characteristics or fixed effects are comprised in the wider included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE 4

ANALYSIS OF THE CHANGES IN COMMITTED LENDING AT THE INTRODUCTION OF DYNAMIC PROVISIONING IN 2000:Q3 ACROSS BANKS AND FIRMS

Model	(1)	(2)	(3)	(4)	(5)	(6)
Dynamic Provision (1998:Q4)$_b$ [=DP$_b$]	-4.635 ***	-0.546 *	-0.594 ***	-0.152	-4.932 ***	
	(.623)	(.316)	(.15)	(.267)	(.787)	
DP$_b$ * Ln(Total Assets$_b$)	0.273 ***				0.315 ***	
	(.042)				(.057)	
DP$_b$ * Capital Ratio$_b$		0.041			0.041	
		(.037)			(.035)	
DP$_b$ * ROA$_b$			0.202 **		-0.168	
			(.088)		(.107)	
DP$_b$ * Doubtful Ratio$_b$				-0.192	-0.207	
				(.148)	(.144)	
DP$_b$ * Ln(Total Assets$_f$)	0.027				0.043 *	0.043 *
	(.025)				(.025)	(.025)
DP$_b$ * Capital Ratio$_f$		-0.005 **			-0.006 ***	-0.007 ***
		(.002)			(.002)	(.002)
DP$_b$ * ROA$_f$			-0.006 **		-0.003	-0.002
			(.003)		(.003)	(.003)
DP$_b$ * Bad Credit History$_f$				0.039	0.000	-0.003
				(.063)	(.066)	(.065)
DP$_b$ * Ln(1+Number of months with the bank)$_{bf}$					-0.025	-0.046
					(.046)	(.042)
Other Bank Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Firm Relationship Characteristic	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed effects	No	No	No	No	No	Yes
Sample with Multiple Bank-Firm Relationships Only	Yes	Yes	Yes	Yes	Yes	Yes
Sample with Firm Characteristics Only	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Bank, Firm	Bank, Firm	Bank, Firm	Bank, Firm	Bank, Firm	Bank, Firm
Number of Observations	237,905	237,905	237,905	237,905	237,905	237,905

NOTE. -- The dependent variable is the Δlog Commitment (2000:Q1-2001:Q2). Table 2 contains the list of variables for each set of characteristics and Table 1 contains all variable definitions. Coefficients are listed in the first row, robust standard errors that are corrected for clustering at the indicated level are reported in the row below in parentheses, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included. *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE 5

SUMMARY STATISTICS FOR DEPENDENT AND INDEPENDENT VARIABLES USED IN THE LOAN AND FIRM LEVEL ANALYSIS OF THE REMOVAL OF THE FLOOR VALUE OF DYNAMIC PROVISIONING IN 2008:Q4 AND GOING INTO THE CRISIS WITH A CERTAIN LEVEL OF DYNAMIC PROVISION FUNDS BUILT UP IN 2007:Q4

Level of Analysis, *Variable Type* and Variable Name	Unit	Mean	Standard Deviation	Minimum	Median	Maximum
Loan Level						
Dependent Variables (bank - firm; 2008:Q1-2009:Q4)						
Δlog Commitment	-	-0.25	0.75	-2.81	-0.14	2.07
Δlog Drawn	-	-0.22	0.85	-2.94	-0.15	2.62
Loan Dropped?	0/1	0.30	0.46	0	0	1
ΔLong-Term Maturity Rate (>1 year)	-	0.08	0.39	-1.00	0.00	1.00
ΔCollateralization Rate	-	0.05	0.23	-1.00	0.00	1.00
ΔDrawn to Committed Ratio	-	-0.26	0.31	-1.00	-0.23	1.00
Bank Dynamic Provisioning (bank)						
d(<25% Dynamic Provision Funds)(2008:Q3)	0/1	0.42	0.49	0	0	1
Dynamic Provision Funds (2007:Q4)	%	1.17	0.23	0.06	1.14	2.57
Other Bank Characteristics (bank)						
Ln(Total Assets)	Ln(000 Euros)	17.86	1.50	9.10	18.17	19.73
Capital Ratio	%	5.57	1.93	1.72	5.30	73.29
Liquidity Ratio	%	12.37	6.26	0.36	10.64	97.25
ROA	%	1.10	0.56	-0.23	0.97	3.44
Doubtful Ratio	%	1.15	0.67	0.00	0.93	12.05
Commercial Bank	0/1	0.51	0.50	0	1	1
Savings Bank	0/1	0.43	0.50	0	0	1
Bank-Firm Relationship Characteristic (bank - firm)						
Ln(1+Number of months with the bank)	Ln(1+Months)	3.79	1.17	0.00	3.93	5.63
Firm Characteristics (firm)						
Ln(Total Assets)	Ln(000 Euros)	7.95	1.68	2.20	7.74	18.24
Capital Ratio	%	23.55	17.87	0.00	19.34	99.47
Liquidity Ratio	%	4.96	7.81	0.00	2.12	100.00
ROA	%	5.66	7.12	-32.58	4.85	55.88
Bad Credit History	0/1	0.14	0.34	0	0	1
Ln(Age+1)	Ln(1+Years)	2.52	0.70	0.00	2.56	4.93
Tangible Assets	%	25.61	23.72	0.00	18.68	100.00
Loan Characteristics (bank - firm)						
Maturity <1 year	0/1	0.50	0.45	0	0	1
Maturity 1-5 years	0/1	0.25	0.38	0	0	1
Collateralized loans	0/1	0.24	0.40	0	0	1
Ln(Loan amount)	Ln(000 Euros)	5.10	1.52	0.22	4.95	13.90
Firm Level						
Dependent Variables (firm)						
Δlog Commitment (2008:Q1 to 2009:Q4)	-	-0.27	0.53	-2.80	-0.19	1.64
Δlog Drawn (2008:Q1 to 2009:Q4)	-	-0.23	0.58	-2.95	-0.17	2.22
ΔLog Total Assets (2007:Q4 to 2009:Q4)	-	-0.02	0.29	-0.91	-0.03	0.98
ΔLog Employees (2007:Q4 to 2009:Q4)	-	-0.11	0.47	-1.77	-0.05	1.39
Firm Death? (in 2009)	0/1	0.06	0.23	0.00	0.00	1.00
Loan Application Level						
Dependent Variable (bank-firm)						
Loan Application Is Accepted and Granted (2008:M10-2010:M12)	0/1	0.28	0.45	0	0	1

NOTE. -- Table 1 contains all variable definitions. The number observations at the loan level: 1,101,806; at the firm level: 118,616; at the loan application level: 61,139.

TABLE 6

LOAN AND FIRM LEVEL ANALYSIS OF THE EFFECTS OF THE FLOOR REMOVAL OF DYNAMIC PROVISIONING IN 2008:Q4 AND OF GOING INTO THE CRISIS WITH A CERTAIN LEVEL OF DYNAMIC PROVISION FUNDS BUILT UP IN 2007:Q

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Level	Loan										
Dependent Variable	Δlog Commitment (2008:Q1-2009:Q4)	Δlog Commitment (2008:Q1-2009:Q4)	Δlog Commitment (2008:Q1-2009:Q4)	Δlog Commitment (2008:Q1-2009:Q4)	Δlog Commitment (2008:Q1-2009:Q4)	Δlog Commitment (2008:Q1-2009:Q4)	Δlog Commitment (2008:Q1-2009:Q4)	*2-Stage Least Squares* Δlog Commitment (2008:Q1-2009:Q4)	Δlog Drawn (2008:Q1-2009:Q4)	Loan Dropped?	Loan Dropped?
d(<25% Dynamic Provision Funds)(2008:Q3)$_b$	0.070 ***	0.077 ***	0.086 ***	0.094 ***	0.098 ***	0.096 ***	0.100 ***	0.086 ***	0.100 ***	-0.046 ***	-0.038 ***
	(.023)	(.028)	(.028)	(.026)	(.024)	(.03)	(.031)	(.029)	(.029)	(.014)	(.014)
Dynamic Provision Funds (2007:Q4)$_b$	0.096 *	0.144 **	0.130 **	0.160 ***	0.172 ***	0.201 ***	0.191 ***	*0.450* ***	0.198 ***	-0.054 *	-0.057 *
	(.05)	(.066)	(.066)	(.059)	(.058)	(.069)	(.07)	*(.101)*	(.061)	(.03)	(.03)
Other Bank Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Firm Relationship Characteristic	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Characteristics	No	No	No	No	Yes	No	No	No	No	No	Yes
Province and Industry Fixed effects	Yes	Yes	Yes	--	--	--	--	--	--	--	--
Firm Fixed effects	No	No	No	Yes	Yes	Yes	--	--	--	Yes	Yes
Firm * Bank Type Fixed Effects	No	No	No	No	No	No	Yes	Yes	Yes	No	No
Sample with Multiple Bank-Firm Relationships Only	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample with Firm Characteristics Only	No	Yes	No	No	No	Yes	No	No	No	No	No
Cluster	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
Number of Observations	1,101,806	510,582	687,408	687,408	687,408	379,821	687,408	687,408	622,824	1,018,699	1,018,699

Model	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Level	Loan			Firm					Loan Application
Dependent Variable	ΔLong-Term Maturity Rate (>1 year) (2008:Q1-2009:Q4)	ΔCollateralization Rate (2008:Q1-2009:Q4)	ΔDrawn to Committed Ratio (2008:Q1-2009:Q4)	Δlog Commitment (2008:Q1-2009:Q4)	Δlog Commitment (2008:Q1-2009:Q4)	Δlog Total Assets (2007:Q4-2009:Q4)	Δlog Employees (2007:Q4-2009:Q4)	Firm Death? (in 2009)	Loan Application Is Accepted and Granted (2008:M10-2010:M12)
d(<25% Dynamic Provision Funds)(2008:Q3)$_b$	-0.074 ***	0.012 ***	0.028 ***	0.058 ***	0.051 ***	0.007 **	-0.005	0.002	-0.056 ***
	(.021)	(.004)	(.007)	(.015)	(.014)	(.004)	(.006)	(.001)	(.015)
Dynamic Provision Funds (2007:Q4)$_b$	-0.175 ***	0.031 ***	0.013	0.105 ***	0.111 ***	0.025 **	0.027 *	-0.008 *	0.094 **
	(.047)	(.01)	(.015)	(.036)	(.035)	(.011)	(.014)	(.004)	(.042)
Other Bank Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Firm Relationship Characteristic	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Characteristics	--	--	--	Yes	Yes	Yes	Yes	Yes	No
Loan Characteristics	Yes	Yes	Yes	No	Yes	No	No	No	No
Province and Industry Fixed effects	--	--	--	Yes	Yes	Yes	Yes	Yes	--
Firm Fixed Effects	Yes	Yes	Yes	> <	> <	> <	> <	> <	Firm-Time
Sample with Multiple Bank-Firm Relationships Only	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Sample with Firm Characteristics Only	No	No	No	Yes	Yes	Yes	Yes	Yes	No
Cluster	Bank	Bank	Bank	Main Bank	Main Bank	Main Bank	Main Bank	Main Bank	Bank
Number of Observations	687,408	687,408	687,408	118,616	118,616	79,183	71,532	149,304	61,139

NOTE. -- Model 6 corresponds to Equation 1; the adjacent text explains Models 1 to 14. In Model 8 in the first stage we regress *Dynamic Provision Funds (2007:Q4)* on the simulated *Dynamic Provision Funds (2007:Q4)* fixing the bank loan portfolio in 2000:Q3. The estimated coefficient equals 0.772 (0.133) ***. In the second stage the in-this-way instrumented *Dynamic Provision Funds (2007:Q4)* replaces the actual *Dynamic Provision Funds (2007:Q4)*. Model 15 corresponds to Equation 2; the adjacent text explains Models 15 to 19. Model 20 corresponds to Equation 3. Table 5 contains the list of variables for each set of characteristics and Table 1 the definition of all variables. The Ln(Loan Amount) included in the Loan Characteristics is averaged from 2005:Q4 to 2007:Q1. Coefficients are listed in the first row, robust standard errors that are corrected for clustering at the indicated level are reported in the row below in parentheses, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included. "No" indicates that the set of characteristics or fixed effects is not included. "> <" indicates that the set of fixed effects cannot be included (because the regression is cross-sectional at the level of the fixed effects). "--" indicates that the indicated set of characteristics or fixed effects are comprised in the wider included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE 7

ANALYSIS OF THE CHANGES IN COMMITTED LENDING FOLLOWING THE FLOOR REMOVAL OF DYNAMIC PROVISIONING IN 2008:Q4 AND OF GOING INTO THE CRISIS WITH A CERTAIN LEVEL OF DYNAMIC PROVISION FUNDS BUILT UP IN 2007:Q4 ACROSS BANKS AND FIRMS

Model	(1)	(2)	(3)	(4)	(5)	(6)
d(<25% Dynamic Provision Funds)(2008:Q3)$_b$ [=DP$_b$]	-0.392 *	0.098	0.148 ***	0.226 ***	0.380 *	
	(.229)	(.077)	(.15)	(.045)	(.226)	
DP$_b$ * Ln(Total Assets$_b$)	0.032 **				-0.002	
	(.013)				(.012)	
DP$_b$ * Capital Ratio$_b$		0.004			0.009	
		(.013)			(.013)	
DP$_b$ * ROA$_b$			-0.050		-0.074	
			(.048)		(.053)	
DP$_b$ * Doubtful Ratio$_b$				-0.125 ***	-0.134 ***	
				(.029)	(.031)	
DP$_b$ * Ln(Total Assets$_f$)	-0.011 ***				-0.011 ***	-0.006 *
	(.004)				(.004)	(.003)
DP$_b$ * Capital Ratio$_f$		-0.001 **			-0.001 ***	-0.001 ***
		(.0004)			(.0003)	(.0003)
DP$_b$ * ROA$_f$			0.000		0.000	0.001
			(.001)		(.001)	(.001)
DP$_b$ * Bad Credit History$_f$				-0.003	0.002	0.004
				(.01)	(.009)	(.009)
DP$_b$ * Ln(1+Number of months with the bank)$_{bf}$					0.005	0.005
					(.007)	(.006)
Dynamic Provision Funds (2007:Q4)$_b$ [=DPF$_b$]	-0.285	0.147	0.256	0.399 ***	0.166	
	(.275)	(.125)	(.15)	(.08)	(.414)	
DPF$_b$ * Ln(Total Assets$_b$)	0.023				0.007	
	(.016)				(.018)	
DPF$_b$ * Capital Ratio$_b$		0.009			0.004	
		(.017)			(.016)	
DPF$_b$ * ROA$_b$			-0.026		-0.024	
			(.136)		(.139)	
DPF$_b$ * Doubtful Ratio$_b$				-0.148 ***	-0.125 ***	
				(.033)	(.043)	
DPF$_b$ * Ln(Total Assets$_f$)	0.006				0.004	-0.002
	(.01)				(.009)	(.01)
DPF$_b$ * Capital Ratio$_f$		0.000			0.000	0.000
		(.001)			(.001)	(.001)
DPF$_b$ * ROA$_f$			-0.001		-0.001	-0.001
			(.002)		(.001)	(.001)
DPF$_b$ * Bad Credit History$_f$				-0.021	-0.033 *	-0.039 **
				(.018)	(.02)	(.02)
DFP$_b$ * Ln(1+Number of months with the bank)$_{bf}$					0.023 *	0.022 *
					(.014)	(.012)
Other Bank Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Firm Relationship Characteristic	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed effects	No	No	No	No	No	Yes
Sample with Multiple Bank-Firm Relationships Only	Yes	Yes	Yes	Yes	Yes	Yes
Sample with Firm Characteristics Only	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Bank, Firm	Bank, Firm	Bank, Firm	Bank, Firm	Bank, Firm	Bank, Firm
Number of Observations	379,821	379,821	379,821	379,821	379,821	379,821

NOTE. -- The dependent variable is the Δlog Commitment (2008:Q1-2009:Q4). Table 5 contains the list of variables for each set of characteristics and Table 1 contains all variable definitions. Coefficients are listed in the first row, robust standard errors that are corrected for clustering at the indicated level are reported in the row below in parentheses, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included. *** Significant at 1%, ** significant at 5%, * significant at 10%.

APPENDIX

- FOR ONLINE PUBLICATION -

CALCULATION OF DYNAMIC PROVISIONS

Dynamic provisions are formula based. The total loan loss provisions for a period are the sum of the *Specific* plus *General Provisions*. The per-period (i.e., the flow of) *General Provisions* are computed as:

$$General\ Provisions_t = \alpha \Delta Loans_t + \left(\beta - \frac{Specific\ Provisions_t}{Loans_t}\right) Loans_t \qquad \text{(A.1)}$$

where $Loans_t$ is the stock of loans at the end of period t and $\Delta Loans_t$ its variation from the end of period $t-1$ to the end of period t (positive in a lending expansion, negative in a credit decline). α and β are parameters set by the *Banco de España*, the Spanish banking regulator. α is an estimate of the percent latent loss in the loan portfolio, while β is the average along the cycle of specific provisions in relative terms. Hence the second term is the key counter-cyclical component.

The above formula is in fact a simplification. There are six risk buckets, or homogeneous groups of risk, to take into account the different nature of the distinct segments of the credit market, each of them with a different α and β parameter. These groups (in ascending order of risk) are the following:

i) Negligible risk: Includes cash and public-sector exposures (both loans and securities) as well as interbank exposures;

ii) Low risk: Made up of mortgages with a loan-to-value (LTV) ratio below 80% and exposures to corporations with an A or higher rating;

iii) Medium-low risk: Composed of mortgages with an LTV ratio above 80% and other collateralized loans not previously mentioned;

iv) Medium risk: Made up of other loans, including unrated or below-A rated corporate exposures and exposures to small and medium-sized firms;

v) Medium-high risk: Consumer durables financing; and finally,

vi) High risk: Credit card exposures and overdrafts.

The values for α are (moving from lower to higher risk levels): 0, 0.6, 1.5, 1.8, 2, and 2.5 percent; and those for β: 0, 0.11, 0.44, 0.65, 1.1, and 1.64 percent. These are the parameter values as they were modified in 2005:Q1 (our second policy experiment), after their introduction in 2000:Q3 (our first policy experiment).

The final formula to be applied by each bank is therefore:

$$General\ Provisions_t = \sum_{i=1}^{6} \alpha_i \Delta Loans_{it} + \sum_{i=1}^{6} \left(\beta_i - \frac{Specific\ Provisions_{it}}{Loans_{it}} \right) Loans_{it} \tag{A.2}$$

$$General\ Provisions_t = \sum_{i=1}^{6} \alpha_i \Delta Loans_{it} + \left(\sum_{i=1}^{6} \beta_i Loans_{it} - Specific\ Provisions_t \right) \tag{A.3}$$

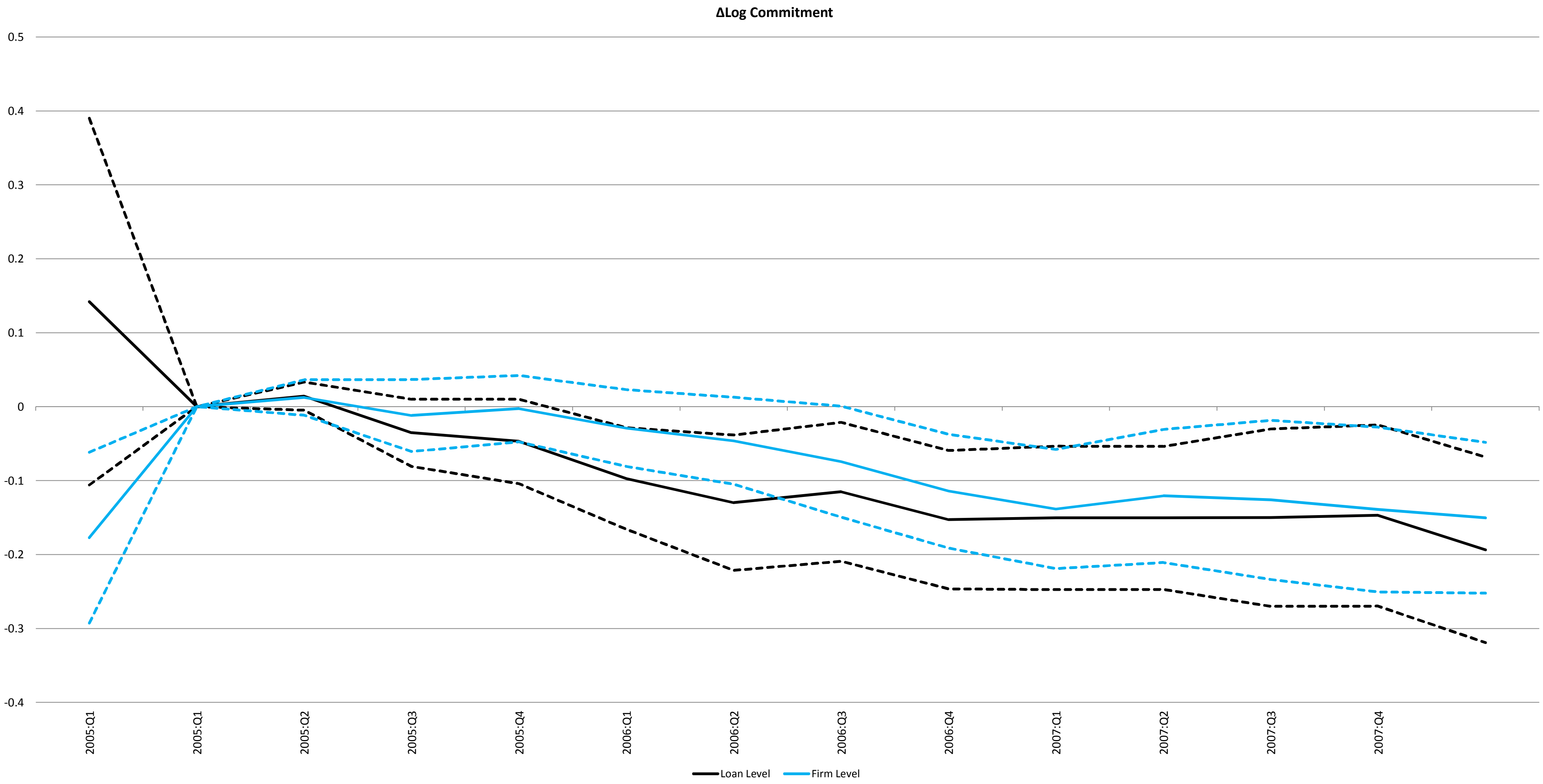
Moreover, there is a ceiling for the fund of general loan loss provisions fixed at 125 percent of the product of parameter α and the total volume of credit exposures. Therefore, the fund of general provisions should be below 125 percent of the latent loss of the loan portfolio. The objective of this ceiling is to avoid an excess of provisioning, which might occur in a long expansionary phase as specific provisions remain below the β component, whereas the α component contributes positively to the accumulation of provisions in the fund. The ceiling is intended to avoid a provision fund that keeps growing indefinitely, producing unnecessarily too high coverage ratios of non-performing loans.

There was also a minimum floor value for the fund of general provisions at 33 percent of the latent loss. This minimum was lowered at the end of 2008 to 10 percent in order to allow for more usage of the general provisions previously built in the expansionary period (our third policy experiment).

TAX TREATEMENT OF DYNAMIC PROVISIONS

Regarding tax treatment, general provisions are tax-deductible up to 1 percent of the increase in gross loans, as long as they are not mortgages. Non-deductible amounts (i.e., those above that threshold) are accounted for as deferred tax assets, because they will become specific provisions in the future, and therefore deductible, when the impairment is assigned to an individual loan. Before 2005 the countercyclical part of the loan loss provisions was not tax-deductible.

FIGURE A.1
ESTIMATES OF TIME-VARYING COEFFICIENT ON THE INDEPENDENT VARIABLE DYNAMIC PROVISION FOR COMMITMENT LENDING



NOTE. -- Solid lines represent the coefficients of Dynamic Provision in Models 8 and 17 in Table A.2 that are estimated with rolling time windows. Dashed lines represent the two standard error confidence band drawn around the coefficient estimates. Black lines are at the loan level, blue lines are at the firm level. Table 1 contains all variable definitions.

TABLE A.1

SUMMARY STATISTICS FOR DEPENDENT AND INDEPENDENT VARIABLES USED IN THE LOAN AND FIRM LEVEL ANALYSIS OF THE MODIFICATION OF DYNAMIC PROVISIONING IN 2005:Q1

Level of Analysis, *Variable Type* and Variable Name	Unit	Mean	Standard Deviation	Minimum	Median	Maximum
Loan Level						
Dependent Variables (bank - firm; 2004:Q4-2006:Q2)						
Δlog Commitment	-	0.01	0.93	-2.77	-0.06	3.05
Δlog Drawn	-	0.01	0.80	-2.52	0.00	2.68
Loan Dropped?	0/1	0.26	0.44	0	0	1
ΔLong-Term Maturity Rate (>1 year)	-	0.00	0.32	-1.00	0.00	1.00
ΔCollateralization Rate	-	0.01	0.19	-1.00	0.00	1.00
ΔDrawn to Committed Ratio	-	-0.25	0.31	-1.00	-0.22	1.00
Bank Dynamic Provisioning (bank; 2004:Q4 to 2005:Q2)						
Dynamic Provision	%	0.05	0.14	-0.18	0.00	0.37
Dynamic Provision Funds / Latent Risk	-	1.33	0.18	0.26	1.38	2.05
Other Bank Characteristics (bank)						
Ln(Total Assets)	Ln(000 Euros)	17.35	1.55	8.97	17.63	19.29
Capital Ratio	%	6.31	3.09	1.78	5.59	53.37
Liquidity Ratio	%	18.18	7.22	0.03	18.35	89.13
ROA	%	0.94	0.50	-3.23	0.89	5.63
Doubtful Ratio	%	0.66	0.40	0.00	0.55	53.56
Commercial Bank	0/1	0.54	0.50	0	1	1
Savings Bank	0/1	0.40	0.49	0	0	1
Bank-Firm Relationship Characteristic (bank - firm)						
Ln(1+Number of months with the bank)	Ln(1+Months)	3.76	1.17	0.00	3.95	5.48
Firm Characteristics (firm)						
Ln(Total Assets)	Ln(000 Euros)	7.49	1.65	1.61	7.30	17.71
Capital Ratio	%	24.60	17.97	0.01	20.74	99.57
Liquidity Ratio	%	5.97	8.71	0.00	2.86	100.00
ROA	%	6.13	7.76	-35.48	5.17	63.16
Bad Credit History	0/1	0.13	0.34	0	0	1
Ln(Age+1)	Ln(1+Years)	2.35	0.78	0.00	2.40	4.90
Tangible Assets	%	26.13	23.32	0.00	19.66	100.00
Loan Characteristics (bank - firm)						
Maturity <1 year	0/1	0.55	0.44	0	1	1
Maturity 1-5 years	0/1	0.24	0.37	0	0	1
Collateralized Loan	0/1	0.19	0.37	0	0	1
Ln(Loan Amount)	Ln(000 Euros)	4.60	1.74	0.00	4.60	13.58
Firm Level						
Dependent Variables (firm)	-					
Δlog Commitment (2004:Q4-2006:Q2)	-	-0.01	0.58	-2.59	-0.03	2.36
Δlog Drawn (2004:Q4-2006:Q2)	-	-0.01	0.64	-2.78	-0.04	2.70
Δlog Total Assets (2004:Q4-2006:Q4)	-	0.17	0.38	-0.92	0.11	1.65
Δlog Employees (2004:Q4-2006:Q4)	-	0.07	0.41	-1.39	0.00	1.61
Firm Death? (2006)	0/1	0.02	0.15	0	0	1
Loan Application Level						
Dependent Variable (bank-firm; 2005:M7-2006:M12)						
Loan Application Is Accepted and Granted	0/1	0.40	0.49	0	0	1

NOTE. -- Table 1 contains all variable definitions. The number observations at the loan level: 884,859; at the firm level: 107,087; at the loan application level: 71,050.

TABLE A.2

LOAN AND FIRM LEVEL ANALYSIS OF THE EFFECTS OF THE MODIFICATION OF DYNAMIC PROVISIONING IN 2005:Q1

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Level	**Loan**									
Dependent Variable	Δlog Commitment (2004:Q4-2006:Q2)	Δlog Commitment (2004:Q4-2006:Q2)	Δlog Commitment (2004:Q4-2006:Q2)	Δlog Commitment (2004:Q4-2006:Q2)	Δlog Commitment (2004:Q4-2006:Q2)	Δlog Commitment (2004:Q4-2006:Q2)	Δlog Commitment (2004:Q4-2006:Q2)	Δlog Drawn (2000:Q1-2001:Q2)	Loan Dropped?	Loan Dropped?
Dynamic Provision(2004:Q4-2005:Q2)$_b$	-0.111 **	-0.120 **	-0.124 **	-0.108 **	-0.040	-0.115 **	-0.045	-0.100 *	0.033	0.046
	(.047)	(.054)	(.056)	(.048)	(.049)	(.048)	(.053)	(.0563)	(.037)	(.037)
Other Bank Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Firm Relationship Characteristic	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Characteristics	No	No	No	No	Yes	No	No	No	No	Yes
Province and Industry Fixed effects	Yes	Yes	Yes	--	--	--	--	--	--	--
Firm Fixed Effects	No	No	No	Yes	Yes	Yes	--	--	Yes	Yes
Firm * Bank Type Fixed Effects	No	No	No	No	No	No	Yes	Yes	No	No
Sample with Multiple Bank-Firm Relationships Only	No	No	Yes	Yes	Yes	Yes	Yes	.	Yes	Yes
Sample with Firm Characteristics Only	No	Yes	No	No	No	Yes	No	No	No	No
Cluster	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
Number of Observations	884,859	460,885	543,499	543,499	543,499	334,631	543,499	480,359	750,735	750,735

Model	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
Level	**Loan**			**Firm**					**Loan Application**
Dependent Variable	ΔLong-Term Maturity Rate (>1 year) (2004:Q4-2006:Q2)	ΔCollateralization Rate (2004:Q4-2006:Q2)	ΔDrawn to Commited Ratio (2004:Q4-2006:Q2)	Δlog Commitment (2004:Q4-2006:Q2)	Δlog Commitment (2004:Q4-2006:Q2)	Δlog Total Assets (2004:Q4-2006:Q4)	Δlog Employees (2004:Q4-2006:Q4)	Firm Death? (in 2006)	Loan Application Is Accepted and Granted (2005:M7-2006:M12)
Dynamic Provision(2004:Q4-2005:Q2)$_b$	-0.065	0.022 **	0.009	-0.074 *	-0.039	0.003	0.014	-0.004	-0.003
	(.064)	(.011)	(.057)	(.038)	(.033)	(.02)	(.022)	(.006)	(.046)
Other Bank Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Firm Relationship Characteristic	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Characteristics	--	--	--	Yes	Yes	Yes	Yes	Yes	No
Loan Characteristics	Yes	Yes	Yes	No	Yes	No	No	No	No
Province and Industry Fixed effects	--	--	--	Yes	Yes	Yes	Yes	Yes	--
Firm Fixed Effects	Yes	Yes	Yes	> <	> <	> <	> <	> <	Firm-Time
Sample with Multiple Bank-Firm Relationships Only	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Sample with Firm Characteristics Only	No	No	No	Yes	Yes	Yes	Yes	Yes	No
Cluster	Bank	Bank	Bank	Main Bank	Main Bank	Main Bank	Main Bank	Main Bank	Bank
Number of Observations	543,499	543,499	327,233	107,087	107,087	79,877	68,737	132,634	71,050

NOTE. -- Model 6 corresponds to Equation 1; the adjacent text explains Models 1 to 13 . Model 14 corresponds to Equation 2; the adjacent text explains Models 14 to 18. Model 19 corresponds to Equation 3. The instrumentation of Dynamic Provision is explained in Equation 3 and adjacent text. Table A.1 contains the list of variables for each set of characteristics and Table 1 the definition of all variables. The Ln(Loan Amount) included in the Loan Characteristics is averaged from 2004:Q4 to 2005:Q4. Coefficients are listed in the first row, robust standard errors that are corrected for clustering at the indicated level are reported in the row below in parentheses, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included. "No" indicates that the set of characteristics or fixed effects is not included. "> <" indicates that the set of fixed effects cannot be included (because the regression is cross-sectional at the level of the fixed effects). "--" indicates that the indicated set of characteristics or fixed effects are comprised in the wider included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE A.3

ANALYSIS OF THE CHANGES IN COMMITTED LENDING AT THE MODIFICATION OF DYNAMIC PROVISIONING IN 2005:Q1 ACROSS BANKS AND FIRMS

Model	(1)	(2)	(3)	(4)	(5)	(5)
Dynamic Provision(2004:Q4-2005:Q2)$_b$ [=DP$_b$]	-1.986 ***	0.133	-0.135	0.159	-4.736	
	(.658)	(.323)	(.15)	(.716)	(16.505)	
DP$_b$ * Ln(Total Assets$_b$)	0.108 ***				0.249	
	(.039)				(.778)	
DP$_b$ * Capital Ratio$_b$		-0.039			-0.037	
		(.051)			(.186)	
DP$_b$ * ROA$_b$			0.035		-0.172	
			(.1)		(.324)	
DP$_b$ * Doubtful Ratio$_b$				-0.394	0.955	
				(1.063)	(6.099)	
DP$_b$ * Ln(Total Assets$_f$)	0.010				0.018	0.002
	(.015)				(.068)	(.015)
DP$_b$ * Capital Ratio$_f$		-0.001			-0.001	-0.001
		(.002)			(.003)	(.002)
DP$_b$ * ROA$_f$			-0.002		-0.002	-0.002
			(.002)		(.002)	(.002)
DP$_b$ * Bad Credit History$_f$				-0.028	-0.024	-0.024
				(.05)	(.099)	(.036)
DP$_b$ * Ln(1+Number of months with the bank)$_{bf}$					0.024	0.004
					(.038)	(.013)
Other Bank Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Firm Relationship Characteristic	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed effects	No	No	No	No	No	Yes
Sample with Multiple Bank-Firm Relationships Only	Yes	Yes	Yes	Yes	Yes	Yes
Sample with Firm Characteristics Only	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Bank, Firm	Bank, Firm	Bank, Firm	Bank, Firm	Bank, Firm	Bank, Firm
Number of Observations	334,631	334,631	334,631	334,631	334,631	334,631

NOTE. -- The dependent variable is the Δlog Commitment (2004:Q4-2006:Q2). Table A.1 contains the list of variables for each set of characteristics and Table 1 contains all variable definitions. Coefficients are listed in the first row, robust standard errors that are corrected for clustering at the indicated level are reported in the row below in parentheses, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included. *** Significant at 1%, ** significant at 5%, * significant at 10%.