The Impact of Alternative Forms of Bank Consolidation on Credit Supply and Financial Stability*

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Abstract

Between 2009 and 2011, the Spanish banking system underwent a restructuring process based on consolidation of savings banks. The program's design allows us to study how alternative forms of consolidation affect credit supply and financial stability. We show that banks consolidating via mergers or business groups are ex-ante comparable in terms of local market's overlap, financial and economic characteristics. We find that, relative to business groups, the market power of merged banks produces a contraction in credit supply, higher interest rates, but also a reduction in non-performing loans. To determine the welfare effects of consolidation, we estimate a structural model of credit demand and supply. In our framework, banks compete on interest rates and can ration borrowers. We also allow borrower surplus to depend on banks' survival. Through counterfactuals, we quantify cost efficiencies and improvements in financial stability that consolidation should deliver to outweigh welfare losses from reduced credit supply.

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1. Introduction

In banking systems featuring many undiversified banks, fierce competition may give rise to excessive risk taking. If bad risks then translate into problematic loans, public intervention drawing on government funds and, hence, taxpayers' money, may become necessary to rescue troubled banks. A structural policy that is often considered by regulators to solve the problems of over-banked systems consists in fostering bank consolidation (Corbae and Levine, 2018). This happened in Europe, where, after the recent financial crisis, the banking sector of many countries was significantly affected by restructuring measures (European Commission, 2017). It also happened in the United States, where the Federal Deposit Insurance Corporation (FDIC) auction process was used after the crisis to resolve insolvent banks, equivalent to a regulator-induced consolidation process (Allen, Clark, Hickman, and Richert, 2019). Finally, it happened in Japan, where after the non-performing loans (NPL) crisis of the late 1990s, the government injected public capital into the banking sector and advised banks to merge (Hoshi and Kashyap, 2004).

Financial regulators' case for bank mergers is supported by the presumption that consolidation makes troubled institutions more capable to absorb losses. However, the literature has established that, after a merger, banks restrict their credit supply, especially at the expense of small and medium firms (SME) (see, among others, Berger, Saunders, Scalise and Udell, 1998; Peek and Rosengren, 1998; Sapienza, 2002; Bonaccorsi di Patti and Gobbi, 2007; Degryse, Masschelein and Mitchell, 2011). Even though these costs could be compensated by the organizational and informational efficiencies produced by consolidation (Houston, James and Ryngaert, 2001; Focarelli and Panetta, 2003; Panetta, Schivardi and Shum, 2009; Erel, 2011), it is unclear what the overall effect of consolidation is for the economy.[1]

We study how alternative forms of consolidation can differentially balance the benefits and the costs of integration. We compare traditional mergers to bank business groups. In the latter, individual banks that remain legally independent delegate to a central unit some of their functions, such as risk management operations. Risk management requires large investments, thus the presence of a central unit allows banks to install information processing technologies that

[1] A complementary strand of this literature studies how bank mergers mediate the propagation of financial shocks (see, e.g., Petersen and Rajan, 1995; Scharfstein and Sunderam, 2016; Favara and Giannetti, 2017; Giannetti and Saidi, 2019).

would not be feasible absent the deal. At the same time, business groups are less likely to give rise to market power than mergers, because sharing risk management does not necessarily translate into implementing the same lending policies. The risk management unit generates information on borrowers' credit merit, but the use of that information may well differ across legally independent banks. This makes coordination of lending policies more difficult than in a full-fledged merger.

The literature is silent regarding the quantification of the relative merits of different integration modes, and this is true not only in banking. With the exception of Gugler and Siebert (2007), who compare mergers and research joint ventures in the semiconductor industry, to our knowledge, there is no other study that deals with this question. This is unfortunate, especially because of the implications that banking consolidation programs have for taxpayers. However it is not surprising, given the challenges posed by the identification of the effects of alternative modes of integration on the exercise of market power and the production of efficiencies.

We fill this gap in the context of the Spanish savings banks sector consolidation program (the program from now on). In the years before the 2008 crisis, head-to-head competition and weak governance led savings banks to take poor investment choices, as exemplified by the hoarding of credit to the construction sector that ultimately led to a NPL problem. Between 2009 and 2011, the program led to a consolidation wave in the Spanish savings banks' sector by which the number of these banks went from 37 to 12. Banks could choose to integrate doing a standard M&A or a business group, but the choice between the two modes was largely driven by regional politics. Indeed, savings banks' governing bodies featured a high representation of regional public authorities, who favored consolidation via M&A between savings banks headquartered within their region of influence and avoid losing control of the merged entity.

Our empirical analysis documents a novel trade-off by comparing standard M&A to business group consolidation. On the one hand, M&A reduce credit supply and increase interest rates. On the other hand, they significantly reduce the amount of NPL in the economy, and thus improve financial stability. These results are explained by the differential market power effect exerted by M&A compared to business groups, and not by differences in the efficiencies produced by the two consolidation modes. Finally, we quantify the welfare effects of the program by means of a structural model, contributing to the recent literature applying equilibrium frameworks from empirical industrial organization to financial markets (Egan, Hortaçsu and Matvos, 2017; Crawford, Pavanini and Schivardi, 2018).

After the crisis that hit the country in 2008, the government gave troubled savings banks the possibility of obtaining public capital in exchange of the submission of a consolidation plan. The other banks could simply consolidate. Between November 2009 and December 2010, virtually all savings banks performed an operation of consolidation. The value of the assets of these institutions amounted to about 1,300 billion Euro (BE), a figure comparable to the total value of US M&A transactions across industries in 2009 and 2010 combined.[2]

In our empirical analysis, we compare the credit supply and the credit performance of business groups and M&A banks, before and after the start of the consolidation program. Our testable prediction is that the market power effect is stronger for M&A. The crucial difference between M&A and business group banks is that the latter remained stand-alone legal entities. This makes the organizational structure of a business group less centralized than that of a M&A. Stein (2002) shows that the loan officer of a decentralized organization will rely more heavily on soft information when setting lending conditions, possibly impairing the coordination of credit policies that is fundamental for the exercise of market power. The results we find are consistent with this intuition.

Our main data source is the Banco de España Central Credit Register, which allows us to observe the stock of credit for the virtual universe of bank-firm relationships in Spain. We complement this information with bank-level data on the interest rate set by banks on newly issued loans together with banks' and firms' balance sheets. The final dataset we use for estimation has 543,154 firm-bank relationships and 396,534 non-financial corporations between November 2007 and November 2011.

We develop our tests in two steps. First, we empirically analyze the determinants of the choice to do a M&A as opposed to a business group. We find that this decision is not correlated with savings banks' province-level overlap at the time the program started. However, it is correlated with overlap in the provinces where savings banks have their main areas of influence, or headquarters. To establish this result, we look at province-level overlap in January 1995, a few years after the regulatory ban on the opening of new branches across provinces was lifted. Second, we compare M&A and business group banks along a set of observable characteristics that are likely to drive the

[2]See www.statista.com/statistics/420990/value-of-merger-and-acquisition-deals-usa/.

decision to team up in a consolidation. We show that there is no systematic evidence of assortative matching based on observables. By doing all this, we confirm empirically the importance of local politics in the choice of the form of consolidation.

We then study the differential effect of bank M&A and bank business groups on credit supply and the cost of credit. During the period between November 2009 and November 2011, the credit balance of a given firm dealing with a M&A bank reduced by 19.4% when compared to that of a similar firm dealing with a business group bank, or about 45,000 euro per firm. For these results, we exploit the variation arising from the credit conditions applied to firms with the same size and within the same period, SIC-3 industry, and province. Bank fixed effects then absorb any other difference in savings banks characteristics before the program started. We also find that a loan of less than one million euro granted by a M&A bank is 17.8 basis points (bp) more expensive than that of similar size granted by a business group bank. In the interest spread specifications, we use time fixed effects to control for macroeconomic and aggregate shocks that affect credit demand or supply, and bank fixed effects to account for bank-specific shocks. Taken together, these results establish the effects produced by M&A banks' differential exercise of market power on credit supply.

To determine the differential impact of M&A and bank business groups on financial stability, we study the performance and composition of loan portfolios. We first construct the CoVaR (Adrian and Brunnermeier, 2016) of the Spanish banking system, which gives us the value at risk of the financial system conditional on a bank being under distress based on the evolution of its bond yields. We show that the increase of a given bank's NPL ratio significantly raises the contribution of this institution to the risk of the banking system. We then find that, after the program started, M&A banks report less NPL than business group banks. Specifically, the share of firm credit that, after the program, turns out to be non performing is about 3 percentage points (pp) less for M&A banks than for business group banks. For these results, we exploit variation coming from borrowers with the same size, SIC-3 industry and province. Thus, the credit supply contraction produced by M&A banks' market power comes with an improvement in their selection of borrowers. To support this result, we look at loan portfolios. We find that the differential reduction in credit extended by M&A banks, as compared to business groups, was significantly larger for ex-ante risky firms. This is in line with the more pronounced use of hard information by more centralized organizations, like M&A bank groups, conjectured by Stein (2002).

Our findings are consistent with the results of a model of credit supply with selection building on Einav and Finkelstein (2011), by which we illustrate the trade-off triggered by market power between a reduction in credit supply and a better selection of borrowers. We capture a situation in which competition encourages banks to chase bad risk by assuming increasing average and marginal costs schedules. In this framework, moving from a competitive allocation to an allocation with market power causes a restriction of credit supply but also an improvement in borrowers' selection (as captured by lower costs). The reason is that, in any allocation, the marginal borrower is worse than the inframargainal ones. Documenting this trade-off contributes to a growing literature studying the effects of imperfect competition in selection markets, both theoretically (Lester, Shourideh, Venkateswaran, and Zetlin-Jones, 2019) and empirically in insurance (Starc, 2014) and credit markets (Adams, Einav, and Levin, 2009; Einav, Jenkins, and Levin, 2012; Allen, Clark, and Houde, 2013). Relative to the extant empirical work, we are the first to provide evidence of the effect of a country-wide consolidation program on borrowers' selection.

Finally, we quantify the impact of the trade-off between market power and selection on welfare. We develop and estimate an equilibrium model with borrowers' demand for credit from differentiated banks, where banks compete à la Bertrand-Nash on interest rates and decide on borrower rationing (see Crawford, Pavanini and Schivardi, 2018).[3] We use the model's estimates and equilibrium assumptions to simulate a scenario with M&A and business groups, and compare welfare (borrower surplus and bank profits) in the pre-program (benchmark) period and in the period with M&A and business groups. The counterfactual with M&A and business groups based on estimates obtained in the benchmark produces changes in quantity and price of credit that are quantitatively comparable to those we obtain in the reduced-form analysis. Moreover, savings banks' marginal costs increase in the quantity of credit, which is consistent with banks' marginal borrower being riskier than the infra-marginal ones in the benchmark.

Our structural framework provides two methodological contributions. First, on top of banks' pricing competition, we also model banks' decision to reject borrowers above an endogenous threshold of expected default risk. This introduces choice-set heterogeneity across borrowers based on their degree of risk, in the spirit

[3]There is a long literature in industrial organization that uses pre-merger data to simulate the likely effects of mergers by using differentiated products models with price setting behavior – see, among others, Berry and Pakes (1993); Hausman, Leonard, and Zona (1994); Werden and Froeb (1994); Nevo (2000); and, more recently, Gowrisankaran, Nevo, and Town (2015).

of Sovinsky Goeree (2008). It also allows us to explicitly model lenders' risk taking behavior and rationing, in line with Stiglitz and Weiss (1981). Second, we express borrower surplus not only as a function of borrower's inclusive values, but also of borrower's rejection probability and of banks' default risk. This allows us to quantify how banks' stability impacts on welfare, because lenders' survival gives borrowers a larger choice set and thus increases borrower surplus.

We use the model to quantify the impact of the consolidation program on borrower welfare and the profits produced by banks' new loan business. We distinguish between the short-run and the long-run effects of the consolidation program. In the short-run (that is, absent cost efficiencies), borrower surplus decreases by about 55 million Euro (ME) and total welfare remains fairly unchanged. To simulate the long-run effects of the program, we quantify the reduction in marginal costs or bank default risk that M&A and business groups should deliver, in order to keep borrower surplus at the same level as before consolidation. We find that this would be achieved with a 0.06% reduction in marginal cost, corresponding to 5.4% of its standard deviation, or with a 1.13 percentage points drop in banks' default risk, about half of its standard deviation.

The paper is also related to the strand of the literature studying the trade-off between bank competition and risk taking. On the one hand, Jayaratne and Strahan (1998) find that lifting branching restrictions improves the stability of the banking system. A result similar to what Carlson and Mitchener (2009) find when analyzing the impact of bank competition on financial stability. On the other hand, Jiang, Levine, and Lin (2017) show that an increase in market contestability increases risk taking by banks, which is consistent with the results in Berger and Hannan (1998) and Carlson, Correa, and Luck (2020). We contribute to this debate by analyzing loan-level evidence on the relative impact of alternative forms of bank consolidation on credit supply and financial stability.

2. The savings banks' sector consolidation program

In this section, we describe the main features of the savings banks' sector consolidation program. We also present a conceptual framework to illustrate our testable hypotheses.

2.1. Institutional setting

In the aftermath of the financial crisis that hit the country in 2008, the Royal Decree 9/2009 (*Real Decreto-Ley 9/2009*) of 26 June 2009 (the Law from now on) took action to restructure the Spanish banking sector. The target of the government was the savings banks (*cajas de ahorros*) sector. As in other countries (see European Commission, 2017), these banks played an important role supporting the economic development of local areas, in a context featuring the high representation of regional public authorities into their governing bodies.

By the end of 2009, savings banks' assets represented about 40% of Spanish banking assets (European Commission, 2017). On the verge of the crisis, the sector was plagued by important structural problems. First, tough competition in a highly fragmented market, coupled with weak governance practices, often translated into poor investment choices. As of 2010, savings banks were exposed to the construction sector for a total of 217BE, of which about 100BE were problematic. Second, savings banks faced legal restrictions that complicated their access to capital markets. This meant that they could raise capital only by retaining earnings, and were thus highly dependant on the wholesale funding sector.

To address these issues, the Law gave troubled savings banks the possibility of obtaining public capital from a special fund (Fondo de Reestructuración Ordenada Bancaria, or FROB) in exchange of the submission of a consolidation plan.[4] The savings banks that were not in financial difficulty could simply integrate. The consolidation program went fast, bringing the number of savings banks from 37 to 12 in the span of thirteen months (November 2009–December 2010).[5] The program featured full compliance: savings banks accounting for about 90% of the credit extended in the sector participated in an operation of consolidation between November 2009 and December 2010. The Spanish government also reformed the functioning framework of the savings banks, including placing them into private ownership. The goal was to cut the political influence exerted by the ownership of regional governments, which was considered to be a chief driver of savings banks' risk taking behavior (Cuñat and Garicano, 2010).

The Law allowed savings banks to consolidate either via a M&A or via a *sistema*

[4]If the plan was approved by the Banco de España, FROB subscribed the capital of the new institution on a transitory basis. The recipients had to commit to buying back this capital as soon as possible.

[5]Table B.I reports the list of the operations of consolidation (SIP and M&A) we consider in the empirical analysis.

institucionales de protección (SIP). SIP are a form of business group, featuring analogies and one crucial difference with respect to a standard M&A. We will start with the analogies. First, SIP banks were compelled to set up a new, central risk management system. Second, they were required to establish pacts of full mutual assistance on liquidity and solvency, and were responsible on a consolidated basis for the fulfilment of regulatory requirements. Third, the Law required that SIP last at least ten years, and produce the same efficiencies as M&A.[6] Finally, SIP banks have access to consolidated information on the firms interacting with other savings banks in the same group, so do not need to tap this info from Banco de España.

The key difference between M&A and SIP banks is that the latter remained separate legal entities. This makes the organizational structure of a SIP less centralized than that resulting from a M&A. In modern banking, lending conditions are automatically set by centralized softwares and risk management directives, with little discretion for loan officers. This description well reflects what happens within M&A banks. SIP banks' legal independence may impair coordination of credit policies, due to the possibly different use of the credit-merit analyses produced by the risk management unit.

We now describe how the consolidation program unfolded. The choice between M&A and SIP was critically influenced by regional politics considerations. In the early phase of the program, all M&A took place between savings banks with headquarters in the same region. Fearing the loss of control on banking activities, regional governments stood against across-region M&A (Banco de España, 2017). Countering these political initiatives, the Constitutional Court made clear that the program's chief goal was to foster the stability of the financial system (Méndez Álvarez-Cedrón, 2011). The Banco de España, then, solicited remaining savings banks to form a SIP (Banco de España, 2017). SIP allowed savings banks to consolidate and at the same time preserve legal independence.

Overall, all M&A happened between banks with headquarters within the same region, and all SIP happened between banks with headquarters in different regions. Yet, as we document later, before the start of the program there is considerable variation in the extent to which M&A and SIP banks' operations overlap at the province level across the whole country. Moreover, there is no systematic evidence

[6] In the words of the Banco de España former deputy governor (Javier Aríztegui): "SIP are expected to produce the same organizational improvements, efficiencies, economies of scope, diversification, and quality as traditional M&A. They must do this within the same time period as a classic merger, and must put all the necessary efforts such that these results be perceived by the market as permanent" (December 2010).

of assortative matching based on observable characteristics, or the political parties governing the regions of SIP banks. Indeed, two thirds of SIP took place between savings banks whose main operations were in regions ruled by different parties.

In what follows, since the first merger after Royal Decree 9/2009 took place in November 2009, we will refer to this month as to the start of the program.

2.2. Market power, credit allocation and loan performance

In this section, we use a setting that builds on Einav and Finkelstein (2011) to show that market power can produce a trade-off between the supply of credit and the selection of borrowers.[7]

Assume that banks in the industry offer symmetric loans to borrowers, and that borrowers face a binary choice between taking the loan or not. We denote by $q \in [0, 1]$ the fraction of borrowers (of given observable type) taking a loan, and by $P(q)$ the cumulative distribution of borrowers' willingness to pay, with $P'(q) < 0$. Finally, assume that there is no fixed cost and that $C(q)$ is the convex total cost curve of the industry. We then denote by $MC(q) = C'(q)$ and $AC(q) = C(q)/q$ the marginal cost and average cost curves, respectively.

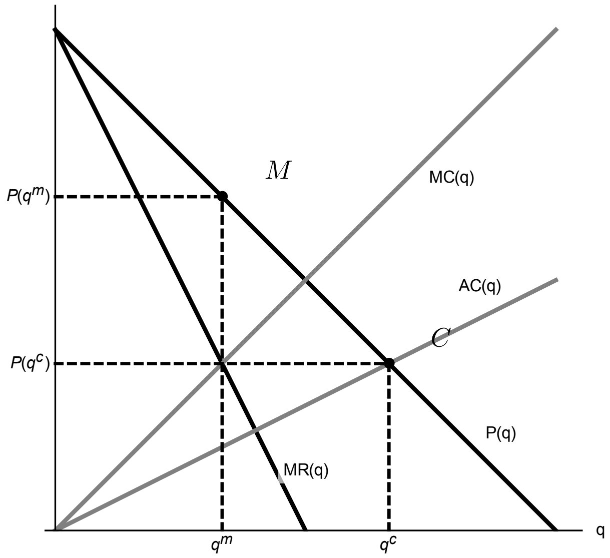
A crucial difference between traditional and selection markets is that in the latter demand and cost are not independent objects. Specifically, the shape of the cost curve is driven by the selection of borrowers in the market. We assume that, by expanding their supply of loans q, banks lend to borrowers with higher probability of default. This means that an increase in q comes with a higher marginal cost and a lower profit margin.[8] More formally, this is equivalent to assuming that the MC and AC schedules slope upward, $MC'(q), AC'(q) > 0$, which gives rise to advantageous selection.[9] Moreover, due to the assumption that $C(q)$ is convex, we have that $MC(q) > AC(q)$ for all $q \in [0, 1]$.

[7] In this framework, banks can ration a firm credit only by adjusting the interest rate, not by rejecting firm's application. In Section 6, we develop and estimate a full-fledged model of oligopolistic bank competition. There, we allow banks to reject a firm based on its observable degree of risk.

[8] This is equivalent to assuming that an expansion in loan supply disproportionally raises borrowing among firms with a greater probability of default. This increases the marginal cost and thus reduces the marginal profit of extending more credit. As discussed in Agarwal, Chomsisengphe, Mahoney, and Stroebel (2018), this could occur because forward-looking firms, who anticipate defaulting in the future, strategically increase their borrowing.

[9] Einav, Jenkins, and Levin (2012) find evidence of advantageous selection in subprime auto loan market, and Mahoney and Weyl (2017) use a model with advantageous selection in their calibrations. While our results would change if the marginal and cost curves slope downwards, the slope of these curves is a matter of empirical investigation. We assume here that it is increasing, and confirm this assumption in our reduced-form and structural analysis.

Figure 1: Demand-supply model



To study the impact of market power within this model, we compare the allocations with perfect competition and monopoly (for simplicity, we impose the linearity of demand and cost curves). Perfect competition means that banks expand their credit supply up to the value of q such that $P(q^c) = AC(q^c)$ (point C in Figure 1). This situation is meant to capture the stance of credit supply in Spain before the consolidation program, where a large number of undiversified savings banks competed chasing bad risk (e.g., the borrowers in the construction sector).

We then conjecture that the M&A wave brings the economy closer to the monopolistic outcome. The monopoly allocation (M in Figure 1) is given by the value of q such that $MR(q^m) = MC(q^m)$, where $MR(\cdot)$ denotes the marginal revenue curve. It comes with lower supply of credit than with perfect competition, but also a better selection of borrowers, implying a reduction in the costs borne by banks.

This simple setup delivers the following trade-off: on the one hand, the market power produced by M&A gives rise to a reduction in credit supply q and an increase in the interest rate $P(q)$. On the other hand, the exercise of market power produces a reduction in costs, independently of additional merger-related cost efficiencies. If consolidation were to produce such efficiencies, however, one should also expect a further reduction in AC and MC for any given q. Thus, the empirical challenge is how to identify the separate effects on costs produced by market power and efficiencies.

To address this challenge, we note that, despite we do not expect SIP to generate a market power effect, they are designed to produce the same level of efficiencies as M&A. That is, M&A and SIP banks should be on the same cost curves so that, absent differences in market power, they deliver the same changes in costs. In the reduced form analysis, then, we estimate the differential impact of M&A and SIP on $P(q)$, q and costs (proxied by NPL). By comparing M&A and SIP, we do two things. First, we identify the change in credit supply for given demand and cost. Second, we separately quantify the reduction in costs produced by M&A's market power with respect to SIP. In the structural analysis, we use our model to quantify the effects of both market power and cost efficiencies.

3. Data and descriptive statistics

Our main data source is the Banco de España Central Credit Register, which collects and maintains information on the stock of credit supplied by Spanish banks. We aggregate the outstanding amount of firm credit with each bank at a monthly basis to obtain total credit (both drawn and undrawn in the case of credit lines). Data on the interest rate applied by banks to newly issued loans is obtained from the Banco de España supervisory data. Different from outstanding credit, interest-rate information is only available at bank-month level, with the possibility of distinguishing between distinct classes of loan size and maturity. We also have information on the volume of NPL reported by banks in relation to a given firm, but cannot distinguish the firm's specific loan that then turns out to be problematic. Finally, we use balance-sheet information collected by the Banco de España in its role as a supervisory authority.

The dataset we use for the empirical analysis comprises information on a total of 543,154 firm-bank relationships and 396,534 non-financial corporations (307,658 in the pre-event period and 280,420 in the post period). The sample period goes from November 2007 to November 2011. We consider the savings banks that participated in a M&A or a SIP between November 2009 and December 2010, which account for about 40% of the total credit in the economy. We then trace the effects of these operations of consolidation between November 2009 and November 2011. The sample period ends in the semester before the one in which Spain received rescue packages to cope with the European sovereign debt crisis.

In what follows, we denote by j the bank group of banks that do a M&A or a SIP. The savings banks that participate in a M&A stop their individual activity at some point in time between November 2009 and December 2010, to operate as a single entity. SIP banks, instead, continued reporting individual information to the credit register until the end of our sample period. As a consequence, between November 2009 and November 2011, we take the group j-level information that is available for M&A, and aggregate the information on the savings banks that are part of each SIP (and that of M&A banks before they start to report information at the group level). In the period between November 2007 to November 2009, we aggregate the information on the savings banks that will later be part of a M&A or a SIP. More information on the construction of the dataset is available in Appendix A.

3.1. Banks, firms and lending relationships

Table I gives the summary statistics related to the savings banks (Panel A) and firms (Panel B) in our dataset. We use these variables as controls in our regressions, and take their value in December 2008 for the period after the program started.

Confirming the high exposure to the real estate and the construction sectors, in Panel A we see that savings banks extended credit accounting for about one-third of the value of their assets to these two sectors only. Nevertheless, as of December 2008, the ratio of NPL over total credit was still relatively low, and equal to about 3.5% on average. We then use the variable Max(Market Share) to measure a savings banks' presence in local markets. To compute it, we take the maximum market share of each savings bank across provinces in December 2008, based on information on all active banks. While the average value of this variable is about 20%, we also have savings banks for which this variable takes a value as small as 1%. Finally, Panel B shows that the firms in our data are rather small, with average assets' value of about 2ME (which corresponds to the asset-based threshold for small firms according to the European Commission Recommendation 2003/361/EC, which we will use in what follows to distinguish between SME and large firms).

In Panels C and D, we report the characteristics of the bank-firm relationships in the two years before (Panel C) and the two years after (Panel D) the consolidation program started. The total volume of credit decreased more in the second period than in the first. The ratio of NPL over total assets and the interest rate spread increased in both periods.

Table I: Summary statistics

Panel A: Banks						
VARIABLES	December 2008					
	Mean	Median	Standard Deviation	5th Percentile	95th Percentile	N
TA (BE)	28.4	13.10	47.60	1.56	173.00	37
Capital Ratio (%)	5.62	5.04	1.71	3.83	9.58	37
NPL (%)	3.61	3.47	1.49	1.65	6.36	37
Credit/Deposits	1.85	1.83	0.36	1.27	2.62	37
ROA (%)	0.49	0.41	0.22	0.24	0.96	37
(Credit to RE and Construction)/TA (%)	30.57	30.08	8.82	14.80	46.68	37
Max(Market Share) (%)	19.59	17.67	14.47	0.96	48.01	37
Panel B: Firms						
VARIABLES	December 2008					
	Mean	Median	Standard Deviation	5th Percentile	95th Percentile	N
TA (ME)	1.89	0.45	5.36	0.04	6.94	280,420
Total Liabilities/TA (%)	72.75	80.04	73.66	18.66	100.00	280,420
Liquid Assets/TA (%)	9.75	3.20	15.78	0.00	43.82	280,420
ROA (%)	4.35	5.53	18.61	-23.22	28.02	280,420
Panel C: Bank-Firm Relationships						
VARIABLES	November 2007–November 2009					
	Mean	Median	Standard Deviation	5th Percentile	95th Percentile	N
ΔLog(Credit)	-0.36	-0.19	2.50	-4.74	4.65	421,991
NPL (%)	5.62	0.00	23.33	0.00	0.00	421,991
Interest rate spread (%) (<1ME)	1.98	1.63	0.88	0.96	3.76	288
Interest rate spread (%) (>1ME)	1.53	1.33	0.87	0.44	3.24	288
Panel D: Bank-Firm Relationships						
VARIABLES	November 2009–November 2011					
	Mean	Median	Standard Deviation	5th Percentile	95th Percentile	N
ΔLog(Credit)	-0.49	-0.21	2.18	-4.39	3.89	370,551
NPL (%)	5.94	0.00	21.27	0.00	0.00	370,551
Interest rate spread (%) (<1ME)	3.22	3.21	0.59	2.32	4.16	300
Interest rate spread (%) (>1ME)	2.44	2.42	0.67	1.36	3.51	300

Notes: This table contains descriptive statistics (mean, median, standard deviation, 5th and 95th percentiles, and number of observations) for bank and firm characteristics (Panels A and B, respectively) as well as for firm-bank credit balances (Panels C and D). Panel A reports information at the level of individual savings banks, Panel B at the level of individual firms, Panels C and D are at the level of a bank group j. TA stands for Total Assets, NPL for Non-Performing Loans, ROA for Return On Assets, RE for Real Estate, and ME for Millions of Euros. Both Panels A and B report the statistics as of December 2008. Panel C reports descriptive statistics on the change in the credit balance between November 2007 and November 2009, the ratio of NPL over total loans for the whole sample of firm-bank pairs, and the average interest rate spread over the three-month Euribor at the bank-month level. Panel D does the same for the period between November 2009 and November 2011. For additional information on the construction of these variables, see Appendix A.

3.2. The systemic impact of NPL

We use NPL to proxy the effects of M&A and SIP on banks' costs. To establish the impact of NPL on financial stability, we use the CoVaR methodology (Adrian and Brunnermeier, 2016). We adapt this methodology to measure the sensitivity of the Spanish banking system bond yields to the increase in the yields of the bonds issued by any single bank.[10] The CoVaR we obtain then gives us the value at risk of the financial system conditional on a bank being under distress based

[10]The CoVaR relies on the growth rate of the market value of total financial assets, however the savings banks in our sample are not listed, so we need to rely on information on bond yields. Appendix C provides a detailed description of the CoVaR methodology and how we implement it.

on the evolution of its bond yields. We then test whether the ratio of NPL over total loans reported by a given bank affects the CoVaR estimated based on the contribution of that bank to the risk of the system. In Table II, we report the results of this analysis.

Table II: NPL and risk spillovers to the domestic banking sector

	(1)	(2)	(3)
VARIABLES	ΔCoVaR Mergers	ΔCoVaR All	ΔCoVaR All
NPL	0.023**	0.039***	0.053***
	[0.011]	[0.008]	[0.006]
Observations	519	519	1,052
R-squared	0.514	0.576	0.651
Bank FE	YES	YES	YES
Bank Controls	YES	YES	YES
Macro Variables	YES	YES	YES

Notes: The set of bank control variables includes: Log(TA), Capital Ratio, NPL, Credit/Deposits, ROA, (Credit to RE and Construction)/TA and (FROB funds)/TA (for information on the construction of these variables, see the data appendix (in Appendix A)). The set of global control variables includes: the VIX index, the (log) changes in Spanish and European bank bond indices and the Spanish banks average bond yield. See Appendix C for a description of the CoVaR methodology and how we construct the dependent variables. Robust standard errors (in brackets) are clustered at year-month-bank level. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level. For additional information on these regressions and the methodology, please see Appendix C.

NPL are indeed important for the stability of the banking system. In columns (1) and (2), we use information from all the savings banks that consolidated between November 2009 and December 2010. The difference between these two columns concerns how we define the dependent variable and more specifically, the pool of banks we use in the estimation of the CoVaR. In column (1), we only consider the savings banks that consolidated between November 2009 and December 2010, whereas in column (2) we use all Spanish banks. In both columns we obtain a positive and significant coefficient. An increase in the NPL ratio of a given bank equal to the standard deviation of the NPL ratio of the banks in our sample would increase the contribution of this bank to the risk of the system by 0.12 pp. This represents 22% of the average CoVaR for the banks in our sample. Results in column (3) are obtained considering all Spanish banks (which explains the higher number of observations), and computing the CoVaR by relying on information related to all banks (as in column (2)). Results are fully consistent with those in columns (1) and (2). These findings are in line with Mayordomo, Rodriguez-Moreno and Peña (2014), who show that the proportion of NPL and leverage have stronger impact on systemic risk than alternative sources of risk, such as derivatives holdings for the United States.

4. Empirical analysis

Our goal is to identify how differences in the market power effect of M&A and SIP banks impact the supply and the performance of credit, controlling for any differences in the efficiencies produced across the two groups. Ideally, we would need three groups of randomly selected banks: some that do M&A, some that do SIP and some that remain untreated. However, practically all savings banks participated in the program, leaving us with two groups: M&A and SIP banks.[11] We then compare these two groups.

4.1. Empirical strategy

We conjecture that the market power effect is stronger for M&A than for SIP, due to the more decentralized structure of SIP (Stein, 2002). Supporting this presumption, Table B.II shows that there are significant differences across banks belonging to the same SIP with respect to the decision on the loan application submitted by the same borrower over a given time period.[12] We also expect that, absent differences in market power, SIP generate the same informational efficiencies as M&A, due to the requirement that both bank group types set up a new risk management unit. In our tests, we provide evidence confirming the validity of this conjecture by exploiting heterogeneity in the presence of M&A and SIP banks at the province level. Finally, in all our tests, we limit to two years the time interval during which we study the effects of the program. Previous literature showed that the cost reductions of bank mergers can take from about two to four years to come about (see, e.g., Focarelli and Panetta, 2003; Erel, 2011), whereas the market power effect occurs within a shorter period.

4.2. The choice between M&A and SIP

In Section 2, we claim that regional politics seemed to play a major role in shaping the choice between M&A and SIP. In this section, we confirm this empirically. First, we establish that the decision to do a M&A, as opposed to a

[11] The Spanish commercial banks are not statistically nor economically comparable to the sample of savings banks, being on average much larger, carrying different business models, and, more importantly, being better capitalized and much less exposed to critical sectors like the real estate industry. However, running our tests on credit conditions and NPL comparing SIP and M&A banks to commercial banks gives results analogous to those we find in Section 5.

[12] We cannot perform the same test for M&A banks, because, different from SIP banks, after consolidation they only report group-level information on credit to the credit registry.

SIP, is not correlated with province-level overlap in November 2009. However, it is correlated with overlap in the provinces where savings banks' have their main areas of influence, or headquarters. Second, we compare M&A and SIP banks along a set of observable characteristics that are likely to drive the decision to team up in an operation of consolidation. We show that there is no systematic evidence of assortative matching based on observables.

Province-level overlap Geographical overlap is a key factor explaining the potential harm of mergers for consumers (Motta, 2004). This is not different for bank mergers (e.g., Erel, 2011). We then study whether local market overlap explains the decision to do a M&A or a SIP during the consolidation program. In the banking literature, the relevant market for antitrust purposes is typically considered to be the province (see, e.g., Guiso, Sapienza and Zingales, 2004), a geographic entity very similar to a U.S. county. Thus, considering geographical overlap at the province level is a natural choice from an economic point of view.

In Table III, we regress the dummy for the decision to do a M&A or a SIP on savings banks' province-level overlap. To measure overlap, we follow Erel (2011) and take the share of province-level credit extended by the second largest savings bank b' of group j in province m over total credit extended in province m:

$$\text{Credit overlap}_{jm} = \frac{\text{Total Credit}_{b'm}}{\sum_{b \in m} \text{Total Credit}_{bm}}. \tag{1}$$

We run the regression using province-level overlap information in November 2009 and January 1995. In 1989, Spain lifted the regulation banning the openings of regional savings banks' branches across local areas. As of 1995, about 80% of savings banks were still located in their original market (Fuentelsaz and Gomez, 2001). We then use market share information in January 1995 to capture savings banks' proximity to their main area of influence, or headquarter. We take January 1995 because it is the first month in which credit information is available in the Spanish credit register.

We find that the choice to do a M&A is correlated with province-level overlap in 1995 (column (2)), but not with province-level overlap in November 2009 (column (1)). The coefficient in column (2) is not only statistically significant (at 10% level), but also economically larger than the coefficient in column (1). This confirms that regional politics was a crucial driver of the decision to prefer a M&A over a SIP, as witnessed by the presence of regional public authorities in savings banks' governing bodies. Savings banks with larger market overlap in

Table III: Geographical overlap of M&A and SIP banks

VARIABLES	(1) November 2009	(2) January 1995
Credit overlap	0.648	2.610*
	[1.020]	[1.480]
Observations	600	600
R-squared	0.308	0.310
Province FE	YES	YES
Bank Controls	YES	YES

Notes: The table reports the results of the regressions that relate the dummy variable that is equal to one for M&A and zero for SIP to measures of credit overlap at the province level as defined in equation (1). In column (1), overlap is taken in November 2009 whereas in column (2) it is taken in January 1995 (the first month with available information from the Spanish credit register). The set of bank controls includes Log(TA), Capital Ratio, NPL, Credit/Deposits, ROA, (Credit to RE and Construction)/TA, Market Share, and (FROB funds)/TA. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level. For additional information, see Appendix A.

their area of influence, as proxied by the credit overlap in their original market in 1995, are disproportionally more likely to do a M&A. However, importantly for our empirical strategy, province-level overlap at the time the consolidation program started does not seem to explain the specific consolidation form chosen.

Financial and economic characteristics In Table IV, we compare M&A and SIP banks' financial and economic characteristics as of December 2008. In Panel A we report the mean values of all individual savings banks' characteristics. In Panel B, we compute the median values of the characteristics within each bank group j, and then average across M&A and SIP. For Panel C, instead, we compute the characteristics of the main savings bank of each group j, based on its total assets, and then average across M&A and SIP. Finally, for Panel D we compute the dispersion of the characteristics of the individual savings banks averaged across the two groups. In the last column of each panel, we run a mean test on the difference of the values of the variables for M&A and SIP banks.

We find that there is no systematic evidence that M&A and SIP banks feature statistically significant differences in their financial or economic characteristics. Except for total assets, which tends to be larger for M&A banks (but the difference is not statistically significant), the two groups feature economically comparable values across the variables we consider, including bank capital.[13] The fact that banks are balanced with respect to the values of NPL over total loans and the exposure to the real estate and construction sector suggests that these banks were balanced with respect to the extent to which they extended crony lending. There

[13]To define bank capital, we follow Jiménez, Ongena, Peydró, and Saurina (2014) and use the ratio between bank equity plus retained earnings over total assets.

Table IV: Comparability of M&A and SIP banks

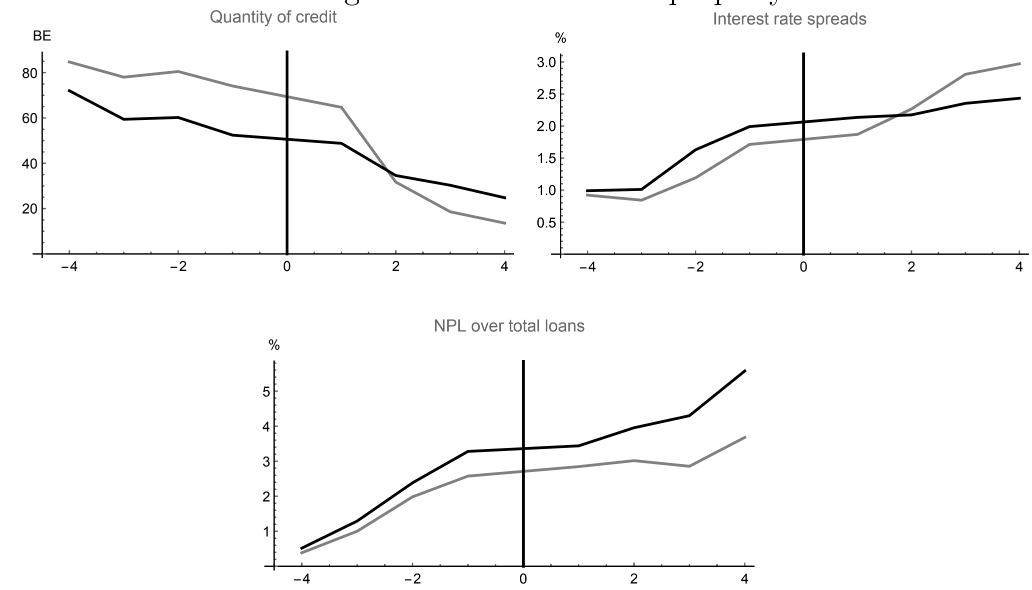
	Panel A: All Savings Banks			Panel B: Median		
VARIABLES	Means		Difference	Means		Difference
	M&A	SIP		M&A	SIP	
NPL (%)	3.720	3.151	0.205	3.825	3.553	0.272
			(0.523)			(0.648)
TA (BE)	36.200	23.400	12.800	37.100	14.800	22.300
			(16.600)			(18.500)
Capital Ratio (%)	4.932	5.888	-0.956	5.004	5.822	-0.818
			(0.596)			(0.594)
ROA (%)	0.462	0.513	-0.051	0.413	0.519	-0.106
			(0.076)			(0.060)
Credit/Deposits	1.829	1.859	-0.030	1.808	1.809	-0.001
			(0.126)			(0.142)
(Credit to RE and Construction)/TA (%)	28.761	31.562	-2.801	28.592	30.737	-2.145
			(3.105)			(3.028)
Max(Market Share) (%)	17.107	21.830	-4.723	17.791	20.975	-3.184
			(5.084)			(6.011)
(FROB funds)/TA (%)	1.016	1.115	-0.099	1.115	1.016	0.099
			(0.528)			(0.528)
	Panel C: Main Bank			Panel D: Standard Deviation		
VARIABLES	Means		Difference	Means		Difference
	M&A	SIP		M&A	SIP	
NPL (%)	4.446	4.991	-0.534	0.596	1.476	-0.880
			(0.820)			(0.596)
TA (BE)	70.200	46.400	23.800	40.500	15.800	24.700
			(43.800)			(27.700)
Capital Ratio (%)	4.457	5.422	-0.966	0.613	1.968	-1.355
			(0.771)			(0.765)
ROA (%)	0.635	0.773	-0.138	0.190	0.229	-0.039
			(0.122)			(0.083)
Credit/Deposits	2.004	2.004	-0.040	0.264	0.270	-0.006
			(0.219)			(0.098)
(Credit to RE and Construction)/TA (%)	26.556	25.195	1.361	4.345	11.010	6.665**
			(8.544)			(2.398)
Max(Market Share) (%)	23.288	31.077	-7.789	7.490	9.411	-1.921
			(10.156)			(3.126)
(FROB funds)/TA (%)	1.115	1.016	0.099	-	-	-
			(0.528)			-

Notes: This table reports bank characteristics for M&A banks and SIP banks at December 2008 (i.e., one year before the bank consolidation process started). All the characteristics are in percentages but the size, which is in billions of euros, and the ratio of credit over deposits. In Panel A we report the average characteristics of the individual savings banks that are part of the consolidation process by type of bank. In Panel B we compare the two types of banks based on the median of each new institution, which are obtained based on the median of the savings banks within a group. In Panel C we compare the characteristics of the main saving bank within each new institution. In Panel D we compare the dispersion within the savings banks forming each new institution based on the standard deviation of each characteristic. The last column of each panel reports the difference between the values in bank characteristics across the two groups of banks, with the values in brackets reporting the robust standard errors associated with a test of difference in the means. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level. For additional information on the construction of these variables, see Appendix A.

is also no evidence of significant differences in the ratio of credit over deposits and market shares, which means that M&A and SIP banks featured similar business models and market penetration before the program started. Finally, since not all of the operations of consolidation were supported by FROB (see Table B.I), it is reassuring that the two groups are comparable with respect to the sums received from the public fund.

We also checked that M&A and SIP banks were balanced in terms of the risk perceived by bank investors, by comparing their pre-sample bond yields. We find that, as of December 2008, the difference in the bond yields of individual savings banks in the two groups was not statistically different from zero (specifically, the

Figure 2: Common trend property



Notes: The plots report the pattern of quantity of credit (top left), interest rate spreads relative to 3-month Euribor (top right), and NPL over total loans (bottom) separately for M&A banks (grey line) and SIP banks (black line) in the time span ranging between 4 semesters before and 4 semesters after November 2009.

bond yield was 4.9% for M&A banks and 5.1% for SIP banks).

All this suggests that there is limited scope for assortative matching based on financial and economic characteristics across the banks in the two groups.

4.3. Unconditional evidence

In Figure 2, we plot the pattern of our main outcome variables across four semesters before, and four semesters after the start of the program. We do this separately for the M&A and the SIP banks in our sample. Specifically, we plot: (i) the average amount of outstanding credit granted to the universe of non-financial corporations (top-left panel); (ii) the average spread between nominal interest rates and the three-month Euribor (top-right panel); (iii) the value of the ratio between the volume of NPL and banks' total loans (bottom panel).

These plots confirm that our main outcome variables satisfy the common trend property. They also provide unconditional evidence that is in line with our predictions, outlined above, on the relative effects of M&A and SIP. In Appendix B, Table B.III reports the results of the multivariate tests of the parallel-trend assumption, and finds results consistent with Figure 2.

In the top-left panel, the evolution of the new credit granted by M&A and SIP banks follows a comparable pattern before November 2009. In the two years before November 2009, M&A banks extend between 15BE and 20BE more credit than SIP banks. Starting from the second semester after November 2009, the sign of the difference reverts. By the end of the fourth semester after November 2009, M&A banks extend approximatively 10BE less credit than SIP banks. That the change in the differential effect starts one semester after the start of the program is to be expected, as most M&A occured at the end of the first quarter and during the second quarter of 2010.

The pattern of interest rate spreads in the top-right panel mirrors that of total credit. M&A and SIP banks' spreads feature a common trend before November 2009. Moreover, M&A banks, on average, apply lower spreads than SIP banks before November 2009, and till the second semester after November 2009. Then, contemporaneously with the reversion in the patterns of total credit, it is SIP banks that apply cheaper average spreads.

Finally, we see a common trend in the pattern of the NPL ratio during the two years before the program. Starting from the second semester after November 2009, the ratio slows down significantly more for M&A than for SIP banks. Finally, possibly because of the start of the European sovereign debt crisis, we observe a spike in the NPL ratio of M&A and SIP banks in the fourth semester after the start of the program.

4.4. Empirical specifications

Main specifications Consider a bank group j dealing with firm i at time t. The baseline econometric model we use for the analysis of bank credit is:

$$y_{jit} = \alpha(\text{M\&A}_j \times \text{Post}_t) + \beta X_{jt-1} + \gamma Z_{it-1} + \zeta \text{FROB}_{jt} + \delta_{kmst} + \eta_j + \epsilon_{jit}. \quad (2)$$

Depending on the specification we consider, we denote by y_{jit} either the growth rate of the volume of total credit in the two years before and after the program started, or the monthly average (log) volume of credit. This second variable is constructed as the average (log) volume of credit over every month between November 2007 and November 2009, and in the period spanning between the announcement of the consolidation (M&A or SIP) and November 2011.

Post_t is the time dummy for the period after the start of the consolidation program. Since y_{jit} is a two-year growth rate, Post_t equals zero from November 2007 till November 2009 and one from November 2009 till November 2011. $\text{M\&A}_j$ is a dummy that equals one if the bank participated in a M&A, 0 if SIP. α is the coefficient of interest. It captures how the program differentially affected the outcome variable for M&A banks relative to SIP banks. All the specifications are estimated including pre-determined control variables, X_{jt-1} and Z_{it-1}. Specifically, X_{jt-1} includes a bank's total assets, capital ratio, NPL, volume of credit over deposits, profitability (ROA), market share, and exposure to the real estate and construction sector. Z_{it-1} includes firm leverage, liquidity, profitability (ROA), and total assets. The value of the variables in X_{jt-1} and Z_{it-1} is taken in 2006 for the period preceding the start of the program, and in 2008 for the period after the program started. Finally, FROB_{jt} denotes the value of FROB's capital injections received by bank group j between 2009 and 2011.

To control for firm-specific shocks, we use industry (k), location (m), size (s), and time (t) fixed effects (δ_{kmst}). This means that we exploit the variation arising from the credit conditions applied to firms with the same size, in terms of assets' decile, and within the same period, SIC-3 industry, and province.[14] To control for bank-specific shocks, we include bank fixed effects (η_j), which absorb any difference in savings banks' characteristics before the program started.

We will use a variant of the model in equation (2) to identify the differential impact of M&A and SIP on savings banks' loan portfolio composition. We split the $\text{Post}_t \times \text{M\&A}_j$ interaction to capture the separate contribution of safe and risky firms to the differential fall in the growth rate of lending produced by M&A with respect to SIP.

Since the information on interest rates is collected at the bank-month level, we aggregate it by maturity and use the following model:

$$w_{jt} = \alpha(\text{M\&A}_j \times \text{Post}_t) + \beta X_{jt-1} + \zeta \text{FROB}_{jt} + \eta_j + \tau_t + \iota_{jt}, \tag{3}$$

where w_{jt} denotes the spread between the nominal interest rate and the three-month Euribor. In this case, since the variable's value is computed at the monthly level, Post_t is equal to zero from November 2007 and October 2009, and one from November 2009 to November 2011. Given the structure of information, the specification only includes bank controls (X_{jt-1}) and no firm control. We also include bank fixed effects (η_j) and monthly fixed effects (τ_t). In an alternative specification we exploit the information on loan maturity. There we augment the model in equation (3) by including maturity fixed effects.

[14]Degryse, De Jonghe, Jakovljevic, Mulier and Schepens (2019) show that industry-location-size-time fixed effects are more appropriate to control for demand differences relative to firm-time fixed effects. By using the latter, we would restrict the sample of firms to consider only those that take credit from multiple banks during the sample period.

For the analysis of NPL, we use:

$$z_{jit} = \alpha \text{M\&A}_j + \beta X_{jt-1} + \gamma Z_{it-1} + \zeta \text{FROB}_{jt} + \delta_{kms} + \epsilon_{jit}. \quad (4)$$

The dependent variable is the proportion of NPL over total loans of a given firm i reported by a bank group j in November 2011.

We consider only the firms that have no credit with the savings banks in our sample during the two years before November 2009. The reason is that we cannot identify the specific loan facility that turns out to be non-performing. If we were to consider the firms with a relationship with a bank before November 2009, it could happen that some NPL reported after November 2009 is related to lending taken before that month. This explains why there is no Post_t dummy, and the use of industry-location-size fixed effects. By using this approach, we limit the possibility that loan refinancing, or evergreening, impairs the interpretation of our analysis. The specification contains firm and bank controls (Z_{it-1} and X_{jt-1}, respectively), and controls for the value of FROB contributions (FROB_{jt}). In Appendix B, we will show that our results on NPL accumulation remain the same when considering the full sample of firms.

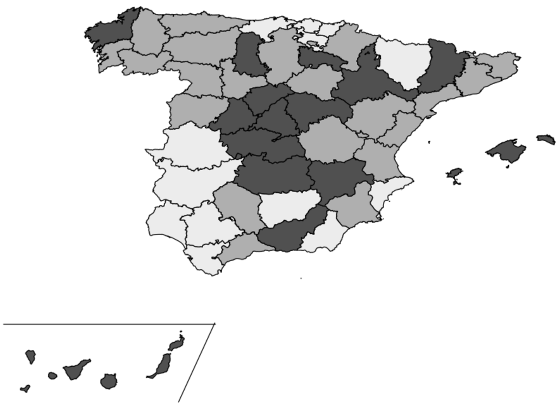
All models are estimated using OLS. For the models in equations (2) and (4), we cluster standard errors at the firm level. For the model in equation (3) clustering is at the level of the interaction of bank-type (M&A, SIP) and month. In Appendix B, we report the results on total lending and NPL when the clustering is at the industry-province-size-bank level.

Specifications exploiting geographic heterogeneity The results in Table III suggest that there is considerable variation regarding the presence of M&A and SIP banks at the province level. We use this source of heterogeneity in the empirical analysis: First, to show that our effects are due to differences in bank organization (SIP and M&A), and not to differences in the size of M&A and SIP banks at the province level. Second, to show that there is no difference in the efficiencies produced by M&A and SIP when the capability to exercise market power is comparably small in the baseline.

In Figure 3, we distinguish between the provinces in which all M&A and SIP banks had a small market share when the program started, and the provinces where they all had larger market shares. In practice, we need a measure for how large a savings bank is compared to the other savings banks in the same province.[15]

[15] Alternatively, we could have run this test by comparing in-market M&A and SIP (see

Figure 3: Geographical distribution of M&A and SIP bank groups



Notes: To construct the distribution of province-level largest market shares, we rank the Spanish provinces based on the market share of the largest savings bank in each province computed in terms of the volume of lending in November 2009. We then take the 25th percentile of this distribution, which corresponds to 13%. The provinces in light grey are those where the market shares of all M&A and SIP banks were smaller than 13% in November 2009. In the provinces in dark grey, instead, at least one of the M&A and SIP banks involved in the program had a market share above 13%, and the largest M&A and SIP bank was in the top 5 banks of the region. The remaining provinces are in intermediate grey.

We rank the Spanish provinces based on the value of the market share of the largest savings bank in each province, computed in terms of the volume of lending in November 2009. We then take the 25th percentile of this distribution, which corresponds to a market share of 13%. We classify a province as one in which M&A and SIP banks had comparably small market shares if all of the M&A and SIP banks operating in that province had a market share smaller than 13%. For the provinces in which market shares are comparably large, we require that at least one of the M&A and SIP banks had a market share above 13% and that the largest M&A and SIP bank was in the top 5 of all banks in the province. We then run our empirical models in (2) and (4) using data from the provinces where M&A and SIP banks are comparably large or comparably small.

5. Empirical results

In this section, we establish the differential impact of M&A and SIP on bank credit, interest rate spreads and the volume of NPL.

Sapienza, 2002). However, separating in-market mergers and out-of-market mergers in the context of the Spanish savings banks is difficult, because most of the savings banks operate in many local markets. Thus, the target and the acquirer can overlap in some markets but not in others.

5.1. Supply of bank credit

To begin with, we study the differential effect of M&A and SIP on the supply of credit in the economy. Columns (1)–(3) and (5)–(6) of Table V report the estimates of equation (2) using as dependent variable the growth rate of the credit granted by the savings banks in our sample. In column (4), we consider the log of the average credit granted by credit institutions over every month of the pre period, and between the announcement of the consolidation (M&A or SIP) and November 2011 for the post period.

Table V: Supply of credit

	(1)	(2)	(3)	(4)	(5)	(6)
		ΔLog(Credit)		Avg Monthly Level	ΔLog(Credit)	
VARIABLES	All	SME	Large	All	Excluding Bankia	Comparably Large
Post x M&A	-0.194***	-0.194***	-0.173	-0.040***	-0.251***	-0.123***
	[0.024]	[0.024]	[0.169]	[0.008]	[0.033]	[0.037]
Observations	792,542	776,962	15,103	768,327	654,910	282,694
R-squared	0.118	0.119	0.221	0.477	0.128	0.111
Industry-Location-Size-Time FE	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES
Bank Controls	YES	YES	YES	YES	YES	YES
Firm Controls	YES	YES	YES	YES	YES	YES

Notes: This table reports the results obtained from a series of regression analyses that relate the variation of credit balance (both drawn an undrawn) of a given firm i in a bank group j to the dummy for M&A and SIP before and after the beginning of the bank consolidation process (November 2009). In columns (1)–(3) and (5)–(6), the dependent variable is the change (log difference) in the credit balance before and after the beginning of the bank consolidation process that we date in November 2009. We consider the variation of credit between November 2007 and November 2009 for the pre-event and between November 2009 and November 2011 for the post-event period. In column (4) we define the dependent variable as the logarithm of the average credit balance granted by credit institutions over every month of the pre-event period and over every month of the period spanning between the announcement of group-j consolidation and November 2011. In columns (1) and (4) we use the whole sample of firms whereas in column (2) we restrict the sample to SME and in column (3) we restrict it to large firms. In column (5) we do not consider Bankia from the sample of savings banks. In column (6) we consider the set of provinces in which the market shares of at least one of the M&A *and* SIP banks operating in that province is above the 25th percentile of the distribution of the maximum market shares at province level, and where the largest SIP and M&A bank was in the top 5 banks of that province in November 2009. The explanatory variable of interest is the interaction of a dummy variable that is equal to one if consolidation is the result of a standard M&A (and zero if consolidation takes place through a SIP) and a dummy variable that is equal one after November 2009. The set of control variables includes bank characteristics such as Log(TA), Capital Ratio, NPL, Credit/Deposits, ROA, (Credit to RE and Construction)/TA, Market Share, and (FROB funds)/TA. We also use the following firm characteristics as control variables: Total Liabilities/TA, Liquidity/TA, ROA, Log(TA). We saturate the different specifications with alternative sets of fixed effects as reported in the table. With industry-location-size-time fixed effects, splitting the full sample of firms in column (1) into SME and Large firms gives rise to additional singletons that we exclude from our regressions; thus, the sum of the observations in columns (2) and (3) does not equal the observations in column (1). Robust standard errors (in brackets) are clustered at firm level. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level. For additional information on the construction of all the variables, see Appendix A.

Compared to SIP banks, M&A banks extend less credit after the start of the consolidation program. Since we control for savings banks' market shares before the program started, and include bank fixed effects, these results cannot hinge on baseline differences in market power or other savings banks' characteristics. Column (1) implies that, compared to SIP banks, M&A banks cut lending by 19.4% or about 45,000 euro per firm.[16] The decentralized nature of SIP bank groups implies that loan officers rely more heavily on soft information when setting

[16]Table B.IV shows the robustness of the results when considering an alternative clustering.

lending exposure, possibly impairing the coordination of credit policies within the group. As a consequence, credit is rationed more by M&A than by SIP banks. We further confirm this interpretation when looking at the differential impact of M&A and SIP on loan portfolios composition.

We observe a significant cut for SME, not for large firms (columns (2)-(3)). This is intuitive, as SME firms are known to be more risky than their large counterparts (see European Banking Authority, 2016). The result contributes to explain the evidence in Banco de España (2016) that, as of 2011, the percentage of micro firms with financing constraints (26%) doubles that of large firms (13%).[17] In column (4), the dependent variable is expressed in terms of average lending per month. In column (5), we check the robustness of our analysis to the exclusion of the credit extended by Bankia from the sample, because, in absolute value, Bankia took the largest contribution from FROB. Our results remain unchanged.

We test for the relevance of potential omitted variables by following the methodology proposed by Oster (2019).[18] She suggests testing whether the identified set for the treatment effect includes zero. We run a version of our specification in column (1) without controls, and compute the bias-adjusted treatment effect. We show that the estimated bound for the treatment coefficient excludes zero. This rejects that the differential effect of M&A on credit supply is driven by omitted variables governing other demand or supply side mechanisms. The details are in Table B.V.

Organizational and geographical differences Column (6) shows that our effects are driven by differences in the organizational structure of M&A and SIP, which imply a differential exercise of market power, and not by the possibility that they are composed by savings banks with different size at the local level. We run our empirical model on the sample of firms that operate in the provinces where M&A and SIP banks have comparably large market shares in November 2009. Our coefficient of interest is negative and statistically significant.

[17]We also study whether these results are the consequence of M&A banks cutting lending disproportionately more on pre-existing relationships at the intensive margin, or denying credit to new borrowers at the extensive margin. We find that both margins are relevant, and therefore decided to not report these results.

[18]Oster (2019) proposes a test for omitted variable bias that uses the information contained in the change in coefficient and R-squared when moving from the uncontrolled to the controlled regression. The methodology, based on Altonji, Elder, and Taber (2005), shows that if selection on the observed controls is proportional to the selection on the unobserved controls, then we can compute an identified set.

5.2. Interest rate spreads

In Table VI, we run equation (3) using bank-month level information on newly issued loans' interest rates. We report the results distinguishing by loan size (less than one million euro, and more than one million euro). In Panel A, we consider the full sample of banks and in Panel B we exclude Bankia.

Table VI: Interest rate spreads

Panel A: All Banks				
	(1)	(2)	(3)	(4)
	OLS, weighted average IR		Weighted OLS, three maturity buckets	
VARIABLES	Loans < 1ME	Loans > 1ME	Loans < 1ME	Loans > 1ME
Post x M&A	0.178***	0.098*	0.253***	0.128
	[0.034]	[0.058]	[0.039]	[0.087]
Observations	586	586	1,751	1,387
R-squared	0.923	0.736	0.800	0.666
Bank FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Maturity FE	NO	NO	YES	YES
Bank Controls	YES	YES	YES	YES

Panel B: Excluding Bankia				
	(1)	(2)	(3)	(4)
	OLS, weighted average IR		Weighted OLS, three maturity buckets	
VARIABLES	Loans < 1ME	Loans > 1ME	Loans < 1ME	Loans > 1ME
Post x M&A	0.102***	0.093	0.106**	0.025
	[0.036]	[0.066]	[0.049]	[0.073]
Observations	537	537	1,604	1,239
R-squared	0.928	0.727	0.823	0.788
Bank FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Maturity FE	NO	NO	YES	YES
Bank Controls	YES	YES	YES	YES

Notes: This table reports the results obtained from a regression analysis in which the dependent variable is the spread of the average monthly interest rate charged by a given bank group j to new loans granted in month t to non-financial institutions over 3-month Euribor. The sample period spans from November 2007 to November 2011. The explanatory variable of interest is the interaction of two dummy variables: a dummy that is equal to one when consolidation takes place through a standard M&A (and zero if consolidation takes place through a SIP) and a dummy variable that is equal to one after November 2009. The set of control variables includes bank characteristics such as Log(TA), Capital Ratio, NPL, Credit/Deposits, ROA, (Credit to RE and Construction)/TA, and (FROB funds)/TA. In addition, we use bank and time fixed effects. The information on interest rates is available for different categories of loan maturity (less than 1 year, between 1 and 5 years, more than 5 years) and size (below and above 1 million euro) buckets. We perform two separate regression analyses depending on the size such that the coefficients in columns (1) and (3) are obtained using interest rates of loans with size below 1 million euro and those in columns (2) and (4) are obtained with loan sizes above 1 million euros. In columns (1) and (2) we perform an OLS regression in which the interest rate is the weighted average across the three maturity buckets, using as weights the new operations within each maturity bucket, so that the unit of observation is bank-month. In columns (3) and (4) we use the interest rate corresponding to each maturity bucket, such that the unit of observation is bank-month-maturity, and estimate the coefficient using a weighted OLS regression with the same controls and fixed effects used in columns (1) and (2) plus maturity fixed effects. In Panel A we consider the full sample of banks. In Panel B, we exclude Bankia. Robust standard errors (in brackets) are clustered at the bank-type (SIP, M&A) month level. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level. For additional information on the construction of all the variables, see Appendix A.

The evidence in the two panels supports the prediction that, compared to SIP banks, M&A banks apply higher interest rate spreads, especially on loans smaller than one million. As is commonly assumed (see, e.g., Banco de España, 2016), it is smaller firms that take loans of this size, implying that this result is consistent with the differential impact of M&A on credit. In columns (1) and (2), we perform an OLS regression in which we take a weighted average of the interest rate across three maturity buckets using as weights the new operations within each bucket (less than one year, between one and five years, and more than five years), so that the unit of observation is at bank-month level. In columns (3) and (4), we use the interest rate corresponding to each maturity bucket, so that the unit of observation is at the bank-month-maturity level, and estimate the coefficients of interest using a weighted OLS regression. The results do not change.

Back-of-the-envelope calculations based on the coefficient in column (1) of Panel A suggest that a loan of less than one million euro granted by a M&A bank is 17.8 bp more expensive than that granted by a SIP bank after November 2009. Thus, the premium charged for this loan size by M&A banks corresponds to 5.3% of the average baseline spread with the 3-month Euribor rate (3.3%).

These results are in line with the reduction in credit documented in Table V, and with the prediction on the stronger market power effect of M&A. Although our results are similar to those in the literature on bank mergers, we obtain them as the differential effect of mergers when compared to business groups. We now look at how the market power effect of M&A impacts on the stability of the banking system.

5.3. Consolidation and financial stability: evidence from NPL and loan portfolios

To study the differential effect of M&A and SIP on financial stability we run equation (4) using information on the volume of savings banks' NPL. The results are in Table VII. In columns (1)–(3) and (5)–(7) the dependent variable is the proportion of NPL over total loans related to a given firm i in bank group j in November 2011. In column (4), we define the dependent variable as the average monthly proportion of NPL between the announcement of each M&A or SIP and November 2011. As mentioned above, we consider the firms that have no credit with the banks in our sample during the two years before November 2009.

Our results suggest that M&A banks report a smaller proportion of NPL than SIP banks. The estimate in column (1) implies that the share of firm credit that turns out to be non performing is about 3 pp less for M&A banks than

Table VII: NPL accumulation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Δ(%NPL)		Avg Monthly Level		Δ(%NPL)	
VARIABLES	All	SME	Large	All	Excluding Bankia	Comparably Large	Comparably Small
M&A	-0.027***	-0.027***	-0.028	-0.016***	-0.030***	-0.013**	-0.008
	[0.004]	[0.004]	[0.020]	[0.003]	[0.004]	[0.006]	[0.007]
Observations	112,560	109,885	2,442	106,524	92,113	42,478	14,315
R-squared	0.221	0.222	0.409	0.236	0.232	0.218	0.307
Industry-Location-Size FE	YES	YES	YES	YES	YES	YES	YES
Bank Controls	YES	YES	YES	YES	YES	YES	YES
Firm Controls	YES	YES	YES	YES	YES	YES	YES

Notes: This table reports the results obtained from a regression analysis in which the dependent variable in columns (1)–(3) and (5)–(7) is the proportion of NPL over total loans of a given firm i in a bank group j in November 2011. We restrict our sample to those bank-firm pairs with zero credit balance in November 2009 and the two years before to guarantee that the proportion of NPL in November 2011 results from credit originated after November 2009. In column (4), the dependent variable is the average proportion of NPL over every month of the period spanning between the announcement of group j consolidation (M&A or SIP) and November 2011. The explanatory variable of interest is the dummy for M&A and SIP. In columns (1) and (4) we use the whole sample of firms whereas in column (2) we restrict the sample to SME and in column (3) we restrict it to large firms. In column (5) we do not consider Bankia from the sample of savings banks. In column (6) we consider the set of provinces in which the market shares of at least one of the M&A *and* SIP banks operating in that province is above the 25th percentile of the distribution of the maximum market shares at province level, and where the largest SIP and M&A bank was in the top 5 banks of that province in November 2009. In column (7), we consider the set of provinces in which the market shares of all the banks operating in a given province is below the 25th percentile of the distribution of the maximum market shares at province level in November 2009. With industry-location-size fixed effects, splitting the full sample of firms in column (1) into SME and Large firms gives rise to additional singletons that we exclude from our regressions; thus, the sum of the observations in columns (2) and (3) does not equal the observations in column (1). Robust standard errors (in brackets) are clustered at firm level. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level. For additional information on the construction of all the variables, see Appendix A.

for SIP banks.[19] Also in this case, the result is essentially driven by the sample of SME. Consistent with Table V, we obtain the same results when considering group-j monthly NPL proportion starting from the announcement of consolidation (column (4)), excluding Bankia (column (5)), and focusing on the provinces where M&A and SIP are comparably large before the program started (column (6)). Finally, whe test for the relevance of potential omitted variables following Oster (2019). We again reject the hypothesis that the differential effect of M&A on NPL accumulation is driven by omitted variables governing other demand or supply side effects (see Table B.V).

Impact on NPL absent market power before the program In column (7) we report the results of a regression in which we restrict the analysis to the provinces where savings banks are comparably small. A conjecture supporting our identification strategy is that, absent market power, SIP and M&A banks generate the same level of efficiencies (thus producing similar effects on the volume of NPL).

[19] We find the same results when standard errors are clustered at the industry-province-size-bank level (Table B.VI), or when using the full sample of firms and both the pre and the post period (Table B.VII).

Then, we run equation (4) using data from the provinces where all M&A and SIP banks' market share was comparably small in November 2009. Since these savings banks are relatively small in the baseline, they are unlikely to have strong market power even after doing a M&A. We find that there is no statistically significant difference in the volume of NPL reported by comparably small M&A and SIP banks. The coefficient is also economically smaller than in column (1).

Overall, these results document that, compared to business groups, the exercise of market power post mergers improves the stability of the banking system. Supporting this interpretation, below we show two things. First, compared to SIP banks, M&A banks extend credit to firms with lower ex-ante risk in the post period. Second, the reduction in NPL reported by M&A banks is not accompanied by an increase in the NPL of the banks that are not involved in the program.

Composition of loan portfolios We now analyze the differential effect of M&A and SIP on the composition of loan portfolios. We classify firms as safe or risky based on the distance from default as resulting from a variation of Altman's Z-score computed for Spanish firms (see Appendix A for the details). We use the firm-level information in December 2006 and December 2008 to obtain the value of the risk indicators for the periods before and after the consolidation program, respectively.

We split the $\text{Post}_t \times \text{M\&A}_j$ interaction to capture the separate contribution of safe and risky firms to the differential reduction in lending produced by M&A with respect to SIP. In columns (1)–(3) of Table VIII, our dependent variable is the growth rate of lending. In column (4), it is the logarithm of the average credit granted by credit institutions over every month of the pre period, and between the announcement of the M&A or SIP and November 2011 for the post period. In this setting, the use of industry-location-risk-time fixed effects implies that our results are identified by comparing the firms with similar risk, obtaining credit in the same time period, and operating in similar industry and location.

We find that the relative impact of M&A and SIP banks on the proportion of NPL documented above can be explained by a differential contraction in the credit supply to risky borrowers. Moreover, there is no statistically significant differential effect on the growth of credit to large safe firms (column (3)). This evidence is consistent with the more pronounced use of hard information by more centralized organizations, like M&A bank groups, conjectured by Stein (2002). Finally, the fact that the coefficients on the $\text{M\&A}_j \times \text{Risky Firm}$ interaction are never statistically significant means that there is no evidence of a statistically

Table VIII: Banks' loan portfolios

	(1)	(2)	(3)	(4)
	ΔLog(Credit)			Avg Monthly Level
VARIABLES	All	SME	Large	All
Post x M&A x Risky Firm	-0.215***	-0.209**	-0.405***	-0.055***
	[0.065]	[0.069]	[0.095]	[0.016]
Post x M&A x Safe Firm	-0.172*	-0.178*	0.173	-0.031
	[0.091]	[0.094]	[0.141]	[0.025]
M&A x Risky Firm	0.017	0.013	0.139	0.022
	[0.048]	[0.047]	[0.166]	[0.016]
Observations	790,774	778,295	14,932	766,523
R-squared	0.062	0.062	0.265	0.432
Industry-Location-Risk-Time FE	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Bank Controls	YES	YES	YES	YES
Firm Controls	YES	YES	YES	YES

Notes: This table extends the analysis in Table V to study the differential proportion of ex-ante safe and risky firms in savings banks' loan portfolios. The variables of interest in our analysis are: (i) the interaction of Post x M&A with a dummy variable that is equal one for safe firms, (ii) the interaction of Post x M&A with a dummy variable that is equal one for risky firms, and (iii) the interaction of the dummy variables denoting risky firms and M&A. Firms are classified as safe or risky based on a variation of an Altman's Z-score for Spanish firms (see Appendix A for the details). We use the information on December 2006 and December 2008 to obtain the firm risk indicators for the pre-event and post-event periods, respectively. In columns (1) and (4) we use the whole sample of firms, in column (2) we use the sample of SME and in column (3) the sample of large firms. The set of control variables are the same as in Table V. We saturate the different specifications with alternative sets of fixed effects as reported in the table. The set of fixed effects we use prevents the estimation of other combinations or interactions of Post, M&A and the dummy variables denoting safe/risky firms. With industry-location-risk-time fixed effects, splitting the full sample of firms in column (1) into SME and Large firms gives rise to additional singletons that we exclude from our regressions; thus, the sum of the observations in columns (2) and (3) does not equal the observations in column (1). One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level. For additional information on the construction of all the variables, see Appendix A.

significant difference in the treatment of risky firms by M&A and SIP banks before the program started.

Spillover effects – loan applications' data To conclude this section, we ask whether the reduction in M&A banks' NPL ratio comes with an increase in the NPL reported by the banks that did not participate in the program (i.e., all the commercial and cooperative banks, and a small number of savings banks). We use the Spanish credit register information on loan applications submitted to a bank by a new borrower. Specifically, we check whether a firm rejected by a M&A (or either a M&A or a SIP) bank then receives a loan by a bank that was not involved in the program, and this loan was non-performing. We do not find any evidence of such spillovers (the results are in Table B.VIII).

6. Welfare analysis

We propose a structural analysis to quantify the welfare implications of our results on credit supply and performance. We develop and estimate an equilibrium model of borrowers' demand for credit from differentiated banks. On the supply side, banks engage in Bertrand-Nash interest rate competition, and can reject borrowers whose observable risk is above a certain threshold. We use the model's estimates and equilibrium assumptions for counterfactuals to simulate scenarios with M&A and SIP and compare welfare (borrower surplus, bank profits) and stability (banks' default probabilities) across scenarios.

6.1. Model

We take as unit of observation a bank $b = 1, ..., B_{mt}$ in a province $m = 1, ..., M$ at a month $t = 1, ..., T$. We assume that borrower i's demand for loans is determined by the following indirect utility function:

$$U_{ibmt} = \underbrace{X'_{bmt}\beta + \alpha P_{bt} + \xi_{bmt}}_{\equiv \delta_{bmt}} + \varepsilon_{ibmt}, \tag{5}$$

where X_{bmt} is a matrix of bank-province-month characteristics, P_{bt} is the average interest rate on that bank's new loans in that month, ξ_{bmt} are unobserved (by the econometrician) bank-province-month attributes, and ε_{ibmt} are IID Type-1 Extreme Value shocks. We allow borrowers to select an outside option, whose indirect utility is normalized to zero, that we define as a set of small fringe banks.

Banks are differentiated firms that compete Bertrand-Nash on interest rates P_{bt} to attract borrowers, and also decide on rationing. Rationing in our context implies that each bank b at time t sets a threshold of expected default rate of borrowers defined as $\overline{F}_{bt}$, such that any borrower above that threshold cannot have access to credit. This threshold is a cutoff in the distribution of expected default rates $F_{bt} \sim TN(\mu_{Ft}, \sigma^2_{Ft})$, which we assume follows a truncated normal distribution with lower bound at 0 and upper bound at 1. It reduces the "size of the market" (i.e. the number of potential borrowers that wouldn't be rejected) for that specific bank-month combination. We use rationing to model the actual demand for credit that a bank can face, net of the rejections it makes. We do not however allow banks to compete on rationing or adjust it in the counterfactual scenarios.[20] We do this to keep the model tractable, and comparable with the reduced form findings,

[20] In practice, $\overline{F}_{bt}$ is computed based on NPL data.

where the reduction in NPL is driven by the drop in quantities due to the market power effect of M&A.

In order to calculate the market shares of bank b in province m at time t, we rank all banks according to their default threshold every month up to the threshold $\overline{F}_{bt}$, from the lowest for bank $\underline{k}$, and assume that default thresholds are public information, such that:

$$\overline{F}_{\underline{k}t} < \overline{F}_{\underline{k}+1t} < ... < \overline{F}_{bt}. \tag{6}$$

In the spirit of Sovinsky Goeree (2008), the formula for bank b's market share in province m at time t can be defined as:

$$\begin{aligned} S_{bmt} =& \exp(\delta_{bmt}) \left[\frac{\Pr\left[F_{bt} \leq \overline{F}_{\underline{k}t}\right]}{1+\sum_k \exp(\delta_{kmt})} + \sum_{\ell=\underline{k}+1}^{b} \frac{\Pr\left[\overline{F}_{\ell-1t} < F_{bt} \leq \overline{F}_{\ell t}\right]}{1+\sum_{k>\ell-1}\exp(\delta_{kmt})} \right] \\ =& \frac{\exp(\delta_{bmt})}{\Phi\left(\frac{1-\mu_{Ft}}{\sigma_{Ft}}\right) - \Phi\left(\frac{-\mu_{Ft}}{\sigma_{Ft}}\right)} \left[\frac{\Phi\left(\frac{\overline{F}_{\underline{k}t}-\mu_{Ft}}{\sigma_{Ft}}\right) - \Phi\left(\frac{-\mu_{Ft}}{\sigma_{Ft}}\right)}{1+\sum_k \exp(\delta_{kmt})} + \sum_{\ell=\underline{k}+1}^{b} \frac{\Phi\left(\frac{\overline{F}_{\ell t}-\mu_{Ft}}{\sigma_{Ft}}\right) - \Phi\left(\frac{\overline{F}_{\ell-1t}-\mu_{Ft}}{\sigma_{Ft}}\right)}{1+\sum_{k>\ell-1}\exp(\delta_{kmt})} \right]. \end{aligned} \tag{7}$$

Banks' equilibrium interest rates are determined by maximizing expected profits:

$$\Pi_{bt} = \left[1 + P_{bt} - MC_{bt}\right] Q_{bt}, \tag{8}$$

where $Q_{bt} = \sum_m^M S_{bmt}\mathcal{M}_{mt}$ is the quantity of loans granted by bank b at time t, $\mathcal{M}_{mt}$ is the total potential amount that could be borrowed in a province-month combination, and MC_{bt} are expected marginal costs, which depend on the quantity of credit. After taking the first order condition with respect to P_{bt} from equation (8), we are able to back out the unobserved (by the econometrician) marginal costs, and express them as a function of quantities:

$$1 + P_{bt} + \frac{Q_{bt}}{\frac{\partial Q_{bt}}{\partial P_{bt}}} = MC_{bt} = \gamma_1 Q_{bt} + \underbrace{\gamma_0 + \gamma_2 Z_{bt} + \tau_b + \omega_{bt}}_{\widetilde{C}_{bt}}, \tag{9}$$

where $Q_{bt}/(\partial Q_{bt}/\partial P_{bt})$ is the markup calculated based on the estimates from the demand model, γ_1 captures the slope of the marginal cost curve, Z_{bt} are bank characteristics varying over time, τ_b are bank fixed effects, and ω_{bt} are IID cost shocks. As we will see, we obtain that marginal costs increase in the amount granted, reflecting the fact that the marginal borrower is riskier than the infra-marginal ones.

6.2. Estimation

We select the major (savings, cooperative and commercial) banks, compute the volume of credit that each of them lends as $\mathcal{Q}_{bmt}$, and then group the total volume of credit granted by all other (small) banks into a single outside option defined as $\mathcal{Q}_{0mt} = \mathcal{M}_{mt} - \sum_{b \in B_{mt}} \mathcal{Q}_{bmt}$.[21] We assume that the market share of the outside option also becomes bank b specific S^b_{0mt}, with a formula equivalent to equation (7). This captures the idea that borrowers above the threshold $\overline{F}_{bt}$ are not able to choose not to borrow, but are simply rejected by the bank. We also need this assumption in order to be able to do Berry (1994)'s inversion and estimate the demand model with instrumental variables based on the following equation:

$$\ln(S_{bmt}) - \ln(S^b_{0mt}) = X'_{bmt}\beta + \alpha P_{bt} + \xi_{bmt}. \tag{10}$$

The specification includes various controls for bank size and profitability in X_{bmt}, and bank and province-month fixed effects. We use as instrument for interest rates P_{bt} the lagged values of NPL. This choice is in line with Egan, Hortaçsu, Matvos (2017), who use lagged charge-offs in their deposit demand estimation exercise. Like charge-offs, lagged NPL affect bank profitability, and thus loan rates. Based on the tests we perform, the instrument is relevant in the first stage, with the expected positive sign. It also satisfies the exclusion restriction, as past bank NPL are likely to be unobserved by borrowing firms. This guarantees that they are uncorrelated with bank attributes ξ_{bmt} observed by borrowers but unobserved by the econometrician.[22]

The sample we use for the estimation includes market shares in terms of loan volumes at the bank-province-month level, whereas bank characteristics and interest rates (measured as the spread between loan rates and the 3 months Euribor) are at the bank-month level. We use the information relative to the new loans extended by all savings banks and the largest commercial and cooperative banks, for a total of 68 banks across 50 provinces. We focus on the 24 months between November 2007 and October 2009, that is, the period before the program started. We do this because only during those months we are able to observe the separate interest rates offered by the banks that will then do a M&A (after the actual mergers take place we can only observe one interest rate for each M&A group).

[21] In our data, the outside option accounts for an average market share of about 12%.

[22] To conduct the Hansen J statistic we use a second instrument (i.e., the NPL lagged two periods) which enables us to run the overindentification test.

Table IX reports descriptive statistics for all variables used in the structural analysis. On top of the variables defined above, D_{bt} denotes our measure of bank's default risk, constructed as the inverse of a distance to default.[23]

Table IX: Descriptives – Structural model

	N	Mean	Standard Deviation	10th Percentile	Median	90th Percentile
Market Share (S_{bmt})	45,061	2.34	4.10	.01	.46	7.62
Total Loan Volume ($\mathcal{M}_{mt}$)	24	9,745.22	1,949.89	7,227.44	9,897.50	12,359.95
Loan Volume (Q_{bt})	1,632	143.31	232.41	5.75	48.89	404.31
Interest Rate (P_{bt})	1,632	5.45	1.05	4.01	5.57	6.74
Bank Default Risk (D_{bt})	1,632	3.52	5.92	1.68	2.80	4.99
Borrowers' Default ($\overline{F}_{bt}$)	1,632	2.70	2.01	.72	2.21	5.49
Marginal Cost (MC_{bt})	1,632	1.03	0.01	1.01	1.03	1.04
Total Assets	1,632	36	74	3	11	80
Capital Ratio	1,632	6.21	2.04	4.04	5.64	9.20
ROA	1,632	0.41	0.28	0.13	0.36	0.78
Credit/Deposits	1,632	1.82	0.52	1.20	1.78	2.50
(Credit to RE and Construction)/TA	1,632	27.66	9.90	13.81	28.34	39.31

Notes: These descriptive statistics are for the main 68 banks in Spain, across 24 months between November 2007 and October 2009, and across 50 provinces. Interest Rate is in percentage points. Loan Volume is in millions of euros. The definition of Bank Default is in footnote 23. Total Assets are in BE. An observation is at the bank-province-month level for Market Share, at the month level for Total Loan Volume, and at the bank-month level for all other variables. For additional information on the construction of these variables, see the data appendix (in Appendix A).

Estimation results are reported in Table X. Assuming a 5% bank's market share and a 5% loan rate (close to the average in the data), borrowers have a demand elasticity of around -2.05. We also find that borrowers tend to favor larger banks, in terms of assets, as well as lenders with a larger share of equity over total assets. Last, we estimate γ_1 in equation (9) using a linear model and find that it is positive and highly statistically significant. In particular, one standard deviation increase in loan volume Q_{bt} corresponds to an increase in marginal cost MC_{bt} of over 43% of its standard deviation.[24] This means that, consistent with the assumption we make in Section 2.2, banks' marginal-cost schedule is increasing.

6.3. Counterfactuals

We use our estimates from the demand and supply models to conduct two counterfactual experiments where we quantify the welfare effects of the consolidation program. Specifically, we simulate the effects of M&A and SIP, as

[23]Following Laeven and Levine (2009), we compute D_{bt} at the bank-time level as SD[ROA]/(Equity/Total assets + ROA), where SD[ROA] is the standard deviation of ROA's monthly value in the 12 months before t. We then winsorize its value between 0 and 1. Despite, technically, D_{bt} is not a probability of default, it is highly correlated with it: the average correlation between the value of D_{bt} and the bond yields of the savings banks in our sample (for which this information is available) is 0.52 between 09/2007 and 09/2011.

[24]Table B.IX in the Appendix reports the results of this regression.

Table X: Demand estimation results

VARIABLES	
Interest Rate	-42.85**
	(21.85)
Log of Total Assets	2.65***
	(0.56)
Capital Ratio (%)	18.66***
	(5.30)
ROA	2.97
	(6.25)
Credit/Deposits	0.25*
	(0.09)
(Credit to RE and Construction)/TA	-0.96
	(0.73)
Bank FE	Yes
Province-Month FE	Yes
Observations	45,061

Notes: We use an instrumental variable regression model in which we instrument the interest rate with the NPL ratio lagged one month. The instrument is relevant (based on the Kleibergen-Paap rk LM statistic), and the Hansen J statistic fails to reject the exclusion restriction. Robust standard errors in brackets. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level. An observation is a bank-month-province. For additional information on the construction of these variables, see the data appendix (in Appendix A).

they actually would have later on happened, using data from the pre-consolidation program period.

We define borrower surplus at the province-month level as follows:

$$E(CS_{mt}) = \frac{1}{\alpha}\log\Bigg[\sum_{k}\exp(\delta_{kmt})\Pr\left[F_{bt} \leq \overline{F}_{\underline{k}t}\right](1-D_{kt}) \\ + \sum_{\ell=\underline{k}+1}^{b}\Bigg[\sum_{k>\ell-1}\exp(\delta_{kmt})\Pr\left[\overline{F}_{\ell-1t} < F_{bt} \leq \overline{F}_{\ell t}\right](1-D_{kt})\Bigg]\Bigg] + C,$$

where C is a constant term derived from the functional form of the surplus equation that cancels out when we take the difference between baseline and counterfactual surplus. The novel feature of this surplus formula is the fact that we weight the mean utility that borrowers gain from each bank in their choice set by the default risk of each bank $(1 - D_{kt})$. This captures the idea that higher stability, that is more solvent banks, can directly benefit borrowers' surplus.

Short-run counterfactual scenario In the first counterfactual we run, we quantify the welfare implications of M&A's market power in the short-run. We assume that neither a M&A nor a SIP produces efficiencies in the form of lower marginal cost or lower default risk of the consolidated banks. SIP banks set interest rates by maximizing the expected profits of each separate entity, similarly to banks that did not consolidate. M&A banks, instead, set loan interest rates by maximizing their joint expected profits. More specifically, if bank b merges with any bank k, its expected profit function will become (the profit function of SIP banks is the same as in the benchmark):

$$\Pi_{bt} = [1 + P_{bt} - MC_{bt}]\, Q_{bt} + \sum_{k \neq b} [1 + P_{kt} - MC_{kt}]\, Q_{kt}. \tag{11}$$

Each M&A bank then internalizes the effect of own credit supply onto the demand of other merging banks. This determines an upward pressure in interest rates relative to the benchmark: M&A banks understand that they can afford an increase in the interest rates they set because some of the borrowers will switch to a merging party.

Long-run counterfactual scenario In the second counterfactual experiment, we allow banks engaging in a M&A or SIP to generate efficiencies. In this way, we simulate a long-term beneficial effect of the consolidation process that can outweigh the market power effect produced by mergers. Notwithstanding the differences in M&A and SIP objective functions, we simulate two potential forms of synergies from consolidation. First, we find the reduction in consolidating banks component of marginal costs $\widetilde{C}_{bt}$ in equation (9) needed to keep borrowers' surplus at the same level as before consolidation. Second, in an alternative case without cost efficiencies, we seek the reduction in consolidating banks' default risk D_{bt} required to keep borrower surplus at the pre-consolidation level.

6.4. Results

Panel A of Table XI reports the average percentage changes in interest rates, quantities, marginal costs, and bank expected profits for the banks engaging in M&A relative to the benchmark, as well as the average percentage changes in borrower surplus and total welfare for all markets. Panel B, instead, reports the average changes in marginal costs and default risk for banks doing M&A or SIP that would keep borrowers' surplus at the pre-consolidation level. All our results relate to banks' new loan business, which is the focus of our analysis.

Short-run results The counterfactual with no efficiencies generates on average an increase in interest rates, a decrease in quantities, a small reduction in marginal costs, and a rise in expected profits for M&A banks. Although they are a direct consequence of M&A market power effect, these results are fairly in line with the reduced form results. Due to the increase in interest rates, after aggregating across banks, provinces and months, we find that total banks' profits increase by 50.47ME. However, in the short run, the increase in interest rates makes borrowers worse off than in the benchmark. Aggregating across months, the total drop in borrower surplus amounts to 55.35ME. We then find a total welfare loss of almost 5ME.

Long-run results We now discuss the effects of M&A and SIP on borrowers' surplus and total welfare in the presence of synergies from consolidation. In the first row of Panel B we show that consolidating banks, to keep borrowers' surplus at pre-consolidation level, would need to reduce on average their marginal costs by 0.06%, corresponding to 5.4% of the standard deviation of marginal costs. In the second row of Panel B we compute by how much banks' solvency should improve to compensate for the loss in surplus caused by the increase in interest rates. We find that, for borrowers to be as well off as in the benchmark, banks' default risk would need to reduce by about half its standard deviation (1.13/2.01).

Table XI: Counterfactual Outcomes

Panel A - Short run		
	M&A Banks	All
% Change Interest Rate	2.83	
% Change Loan Volume	-4.80	
% Change Marginal Costs	-0.01	
% Change Banks Profit	1.15	
% Change Borrower Surplus		-0.96
% Change Total Welfare		-0.04
Panel B - Long run		
M&A & SIP Banks		
% Change in Marginal Costs	-0.06	
Change in Bank Default Risk	-1.13	

Notes: Interest Rate is in percentage points. Loan Volume is in millions of euros. In Panel A all values are averages across bank-month level observations. In Panel B all values are averages across bank-month level observations (for Interest Rate and Loan Volume) and month level observations (for all other variables).

7. Conclusions

Between 2009 and 2011, the Spanish banking system underwent a restructuring process based on consolidation of savings banks. We exploit the institutional design of the consolidation program to study the relative impact of bank mergers and bank business groups on credit supply and financial stability. We unveil a new trade-off. On the one hand, compared to bank business groups, the market-power effect of bank mergers produces a reduction in credit supply and an increase in interest rates, especially to SME. On the other hand, market power causes a reduction in the volume of non-performing loans, thereby improving financial stability. To show that these results are not driven by differences in the efficiencies generated by mergers and business groups, we exploit the province-level variation in the overlap of M&A and SIP banks. Finally, we quantify the short-run and long-run welfare effects of the program by means of a structural model.

The validity of our analysis extends beyond the Spanish case. We already mentioned the American and Japanese restructuring measures in the introduction, and savings banks are widespread in Europe. As of 2009, the German savings banks sector represented about one third of the total banking assets (European Commission, 2017), and it landed into systemic problems during the crisis (International Monetary Fund, 2011). In Italy a number of savings banks needed help after the crisis, suffering problems from NPL accumulation. The claim of policy makers was, and still is, that consolidation can be a means to solve the problems resulting from excessive NPL stockpiling.[25]

We show that bank mergers can be effective in improving financial stability, especially as a remedy to crises produced by banks' excessive risk taking. Our welfare analysis quantifies cost efficiencies and improvements in financial stability that consolidation should deliver, in order to outweigh welfare losses from reduced credit supply.

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A. For Online Publication – Data appendix

The information on loans is obtained from the Banco de España Central Credit Register (CCR). The CCR contains detailed monthly information on the credit position of each Spanish firm with each Spanish bank for all loans above 6,000 euros, including credit lines. Thus, we observe the virtual universe of bank exposures to non-financial corporations. For each loan, we know the size of the credit instrument, and other characteristics such as maturity and collateral. We aggregate the outstanding amount of credit of each firm in each bank at a monthly basis to obtain total credit (both drawn and undrawn in the case of credit lines).

Since the CCR reports the identifier of each bank and firm, we merge the loan-level data with the balance sheets of banks and firms. The data on banks is collected by the Banco de España in its role of banking supervisor. It is used to obtain proxies for bank size (logarithm of total assets), leverage (total liabilities over total assets), risk (NPL over total loans), liquidity (credit to deposits ratio), and profitability (ROA). The CCR is merged with the dataset of the Spanish non-financial firms that respond to the Integrated Central Balance Sheet Data Office Survey (CBI), which contains information from the accounts filed with the mercantile registries for more than 830,000 firms in 2006 and almost 850,000 firms in 2008 (as of the version of the dataset available in March 2020). This dataset also includes information on firms' identifier, industry of operation, and other items of the balance sheet that enable us to obtain proxies for firms' size, leverage and profitability (constructed analogously to those for the banks), liquidity (liquid assets over total assets) and risk (based on a Z-score whose construction we explain below). Moreover, we can identify each bank-firm relationship by aggregating loans within each bank-firm pair. This feature allows us to trace all the changes in credit flows between a given bank and a given firm over time. In addition, the dataset reports information on each bank-firm pair in which either firms have missed to pay back their debt obligations which enables us to compute the ratio of non-performing loans over total loans at bank-firm level. Finally, we use information on the FROB funds made available to each bank to assist with the consolidation, which are obtained from the FROB webpage.

An additional dataset we use consists of all the requests for information made by banks on firms' credit situation to the Spanish CCR. Banks submit these requests when they receive a loan application by a firm to which they have no current exposures. This information enables us to identify firms that are seeking a bank loan as those that submit an application to a bank with which they have no outstanding credit balances. Importantly, given that the CCR contains information on the outstanding credit balances, we can infer whether or not the firm obtained the loan from either a new bank that requested information on the firm or from any other bank (including those with a previous positive exposure). We assume that the loan application is accepted when there is an increase in the outstanding credit balance between the month prior to the request for information and the following three months.

With all these sources of information, we build a panel of both real variables and credit data.[26] We use the balance-sheet items of 37 savings banks that merged after November 2009 leading to 12 new institutions. Note that due to the condolidation program, the individual savings banks that are part of standard M&As stop their individual activity at some point in time between November 2009 and November 2011 and start to operate as a single group. Thus, we need to aggregate in a similar way the credit institutions that are part of M&A and SIP, which continued reporting information at individual savings bank level until the end of our sample period. For this reason, we consolidate the information of savings banks that are part of the new credit institutions during the whole sample period. To this aim, we aggregate each balance-sheet item (total assets, total liabilities, total credit, NPL, total deposits and total income) of all credit institutions that are part of each new banking group and then obtain the corresponding ratio.

Finally, we describe the construction of the credit score we use in Table VIII. The version of Altman's Z-score we use was developed by Amat, Manini, and Renart (2017) for Spanish firms.[27] It is obtained from the following specification:

$$\begin{aligned} Z &= -3.9 + 1.28 * (\text{Current Assets/Current Liabilities}) + 6.1 * (\text{Net Worth/Total Assets}) \\ &\quad +6.5 * (\text{Net Profit/Total Assets}) + 4.8 * (\text{Net Profit/Net Worth}). \end{aligned} \tag{12}$$

We convert this score into a discrete variable that is equal to one if the firm is in the "distress" zone, which occurs when the resulting Z-score is negative, and zero otherwise.

A.1. Variable definition

Bank-level variables

- Capital Ratio: bank equity plus retained earnings over total assets.
- Credit/Deposits: volume of bank credit over volume of bank deposits.
- (Credit to RE and Construction)/TA: volume of bank credit to real estate and construction sectors over total assets.
- (FROB funds)/TA: funds made available by FROB to a savings bank relative to the savings bank's total assets.
- M&A: dummy equal to one if consolidation takes place through a standard M&A and zero if consolidation takes place through a SIP.

[26] Firm level variables and the log change in credit are winsorized such that we set the observations above (below) the 99% (1%) percentiles at the value of the 99% (1%) percentile

[27] See Amat, O., Manini, R., and Renart, M. A., 2017. Credit Concession Through Credit Scoring: Analysis and Application Proposal. Intangible Capital 13, 51–70.

- Market Share: ratio between the credit extended in a given province by a savings bank over the sum of credit extended by all savings banks in that province.
- Max(Market Share): the maximum market share of each savings bank across provinces in December 2008, computed using information on all active banks.
- NPL: the ratio of NPL over total loans.
- Post: dummy variable that is equal to one after the start of the consolidation program (November 2009) and zero beforehand. The exact timing depends on the definition of the dependent variable, as we explain in Section 4.4 and in the tables' notes.
- ROA: EBITDA over total assets.
- Total Assets (TA): bank total assets in billions of euros (BE).

Firm-level variables

- Liquidity/TA: value of firm liquid assets over total assets.
- Risky Firm: dummy equal to one if the Z-score constructed as in equation (12) is negative, and zero otherwise.
- ROA: EBITDA over total assets.
- Safe Firm: dummy equal to one if the Z-score constructed as in equation (12) is positive, and zero otherwise.
- Total Assets (TA): bank total assets in millions of euros (ME).
- Total Liabilities/TA: value of firm liabilities over total assets.

Bank-firm-level variables

- Δ Log(Credit): change in the log value of credit balance between November 2007 and November 2009 (pre-event) and between November 2009 and November 2011 (post-event).
- Loan Application Rejected by M&A Bank: dummy equal to one if firm i applied for a loan to one or more savings banks that did a M&A and this application was rejected.
- Loan Application Rejected by M&A or SIP Bank: dummy equal to one if firm i applied for a loan to one or more savings banks that did a M&A or a SIP and this application was rejected.
- NPL: ratio of NPL over total loans.

B. For Online Publication – Additional tables and figures

Table B.I: Overview of the consolidation program

(1) Announcement Date	(2) Merging parties	(3) New bank	(4) Type	(5) FROB	(6) # Regions
November 2009	Caja Castilla la Mancha, Cajastur	Cajastur	SIP	0.0%	2
March 2010	Caixa Sabadell, Caixa Terrasa, Caixa Manlleu	Unnim	M&A	1.4%	1
March 2010	Catalunya Caixa, Caixa Tarragona, Caixa Manresa	Catalunya Caixa	M&A	1.6%	1
March 2010	Caja España, Caja Duero,	Ceiss	M&A	1.2%	1
April 2010	Caja Navarra, Caja Canarias, Caja Burgos	Banca Cívica(*)	SIP	1.3%	3
May 2010	Unicaja, Caja Jaén	Unicaja	M&A	0.0%	1
May 2010	La Caixa, Caixa Girona	La Caixa	M&A	0.0%	1
June 2010	Caja Murcia, Caixa Penedés, Sa Nostra, Caja Granada,	BMN	SIP	1.3%	4
June 2010	Caja Madrid, Bancaja, Caja Ávila, Caja Segovia, Caja Rioja, Caixa Laietana, Caja Insular de Canarias,	Bankia	SIP	1.5%	6
June 2010	Caixa Galicia, Caixanova,	Novacaixagalicia	M&A	1.6%	1
July 2010	CAI, Caja Círculo de Burgos, Caja Badajoz	Caja 3	SIP	0.0%	3
July 2010	Bilbao Bizkaia Kutxa, CajaSur	Bilbao Bizkaia Kutxa	SIP	1.7%	2

Notes: The table uses information from International Monetary Fund (2012), Banco de España (2015), Banco de España (2017). Column (5) reports the ratio of FROB contributions over the total assets of the new group, in percentage value. Column (6) reports the number of regions in which the institutions involved in the operation of consolidation have their headquarters. (*): Banca Cívica later acquired Caja Sol-Caja Guadalajara in December 2010.

Table B.II: Evidence of un-coordinated lending conditions across SIP banks

	Rejected Application
Bank1	0.200*
	[0.117]
Bank2	0.252*
	[0.131]
Bank3	0.065
	[0.117]
Bank4	0.038**
	[0.016]
Bank5	.
	.
Bank6	.
	.
Observations	1,005
R-squared	0.884
Bank-Firm FE	YES

Notes: In this table, we test whether savings banks within a given SIP have similar lending policies after forming the group. We restrict our sample to savings banks that consolidated through a SIP and to the period between November 2009 and November 2011. Our dependent variable is a dummy variable that is equal to one if (i) a savings bank belonging to a given SIP requested information on a firm between November 2009 and November 2011 and (ii) we do not observe an increase in the firm-bank credit balance. When these conditions are jointly satisfied, we infer that the firm loan application was rejected. The dependent variable is equal to zero when the request of information is followed by an increase in the firm-bank credit balance, which we interpret as a successful loan application. We regress this variable on dummy variables for each specific savings bank (the omitted term refers to one savings bank in each given group) and on SIP group-firm fixed effects. The use of these fixed effects allows us to control for the common treatment of a given firm within the SIP group, such that if all savings banks treat the firm loan application in the same way, the individual savings bank dummy variables should not be statistically significant. Note that due to the use of these fixed effects, our sample is restricted to those observations for which two savings banks within a given SIP group request information on the same firm during the period under consideration. Given that each SIP involves a different number of savings banks, to guarantee confidentiality, we just report the coefficient with lowest p-value within each SIP. A significant coefficient would support the statement that savings banks within a given SIP apply different lending policies to the same firm. Our sample consists of six SIP but due to the lack of observations on common requests of information within each SIP and period, we can only estimate the coefficients for four out of the six SIP in our sample. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level.

Table B.III: Tests on pre-trends for M&A and SIP

VARIABLES	(1) ΔLog(Credit)	(2) OLS, weighted average IR Spread Loans < 1M	(3) Weighted OLS, three maturity buckets Spread Loans < 1M
M&A	-0.036	-0.061	-0.005
	[0.022]	[0.043]	[0.032]
Observations	421,991	299	895
R-squared	0.109	0.860	0.709
Industry-Location-Size FE	YES	NO	NO
Time FE	NO	YES	YES
Maturity FE	NO	NO	YES
Bank Controls	YES	YES	YES
Firm Controls	YES	NO	NO

Notes: Column (1) reports the results obtained from a regression analysis in which the dependent variable is the variation in the credit balance (both drawn an undrawn) of a given firm i in a bank group j between November 2007 and November 2009 (i.e., before the beginning of the restructuring program). The dependent variable in columns (2) and (3) is the spread of the average monthly interest rate charged by a given credit institution j to new loans with size below 1 million euro granted at month t to non-financial institutions over 3-month Euribor. More specifically, in column (2) the interest rate is obtained as the weighted average across three maturity buckets (less than 1 year, between 1 and 5 years, more than 5 years), using as weights the new operations within each maturity bucket, such that the unit of observation is bank-month. In column (3) we use the interest rate corresponding to each maturity bucket, such that the unit of observation is bank-month-maturity and estimate the coefficients using a weighted OLS regression instead of the standard OLS regression we run in columns (1)–(2). The set of control variables in column (1) includes the bank and firm characteristics in Table V whereas in columns (2) and (3) we just use the bank characteristics (as listed in Table V). We saturate the different specifications with alternative set of fixed effects: in column (1), we use industry-location-size-time fixed effects. The specifications in column (2) and (3) include year-month fixed effects, and in column (3) we also add maturity fixed effects. The use of firm or time fixed effects implies that firm controls are not used in columns (2)–(3). Standard errors, in brackets, are clustered at firm level in column (1) and at bank level in columns (2) and (3). One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level. For additional information on the construction of these variables, see the data appendix (in Appendix A).

Table B.IV: Credit volume results – Clustering at the industry-province-size-bank level

	(1)	(2)	(3)	(4)
	ΔLog(Credit)			Avg Monthly Level
VARIABLES	All	SME	Large	All
Post x M&A	-0.194***	-0.194***	-0.173	-0.040***
	[0.022]	[0.022]	[0.154]	[0.011]
Observations	792,542	776,962	15,103	768,327
R-squared	0.118	0.119	0.221	0.477
Industry-Location-Size-Time FE	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Bank Controls	YES	YES	YES	YES
Firm Controls	YES	YES	YES	YES

Notes: This table is analogous to the first four columns in Table V, with the only difference that robust standard errors in brackets are clustered at industry-location-size-time-bank level. With industry-location-size-time fixed effects, splitting the full sample of firms in column (1) into SME and Large firms gives rise to additional singletons that we exclude from our regressions; thus, the sum of the observations in columns (2) and (3) does not equal the observations in column (1). One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level. For additional information on the construction of these variables, see the data appendix (in Appendix A).

Table B.V: Omitted variable test

Panel A		
	(1)	(2)
VARIABLES	ΔLog(Credit)	
Post x M&A	-0.091***	-0.194***
	[0.006]	[0.024]
Observations	819,286	792,542
R-squared	0.000	0.119
Industry-Location-Size-Time FE	NO	YES
Bank FE	NO	YES
Bank Controls	NO	YES
Firm Controls	NO	YES
Identified Set	[-0.225,-0.194]	

Panel B		
	(1)	(2)
VARIABLES	Δ(%NPL)	
M&A	-0.019***	-0.027***
	[0.001]	[0.004]
Observations	124,479	112,560
R-squared	0.002	0.221
Industry-Location-Size FE	NO	YES
Bank Controls	NO	YES
Firm Controls	NO	YES
Identified Set	[-0.027,-0.021]	

Notes: This table reports the results from our baseline specification (column (2)) and from a specification without controls and industry-location-size-time fixed effects (column (1)), using as dependent variable the ΔLog(Credit) (Panel A) and the Δ(%NPL) (Panel B) (for additional details, see Tables V and VII). One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level. We compute the bounds of the identified set recommended by Oster (2019), as given by $\tilde{\beta}$ and $\beta^*(R_{max}, \delta)$, where $\beta^*(R_{max}, \delta) = \tilde{\beta} - \delta \frac{(\dot{\beta}-\tilde{\beta})(R_{max}-\tilde{R})}{(\tilde{R}-\dot{R})}$, $\tilde{\beta}$ and $\tilde{R}$ are the bias-unadjusted estimated coefficient and the R-squared from the model with larger controls (column (2)), respectively, and $\dot{\beta}$ and $\dot{R}$ are the estimated coefficient and the R-squared from the simplest model (column (1)), respectively. We follow the standard test parametrization proposed by Oster (2019) and fix $\delta = 1$ and $R_{max} = 1.3\tilde{R}$. The estimated identified sets are reported at the end of each panel. Both sets exclude zero.

Table B.VI: NPL – Clustering at the industry-province-size-bank level

VARIABLES	(1) All	(2) Δ(%NPL) SME	(3) Large	(4) Avg Monthly Level All
M&A	-0.027***	-0.027***	-0.028	-0.016***
	[0.004]	[0.004]	[0.020]	[0.003]
Observations	112,560	109,885	2,442	106,524
R-squared	0.221	0.222	0.409	0.236
Industry-Location-Size FE	YES	YES	YES	YES
Bank Controls	YES	YES	YES	YES
Firm Controls	YES	YES	YES	YES

Notes: This table is analogous to the first four columns in Table VII, with the only difference that robust standard errors in brackets are clustered at industry-location-size-time-bank level. With industry-location-size fixed effects, splitting the full sample of firms in column (1) into SME and Large firms gives rise to additional singletons that we exclude from our regressions; thus, the sum of the observations in columns (2) and (3) does not equal the observations in column (1). One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level. For additional information on the construction of these variables, see the data appendix (in Appendix A).

Table B.VII: NPL – Sample with all firms

	(1)	(2)	(3)	(4)
		Δ(%NPL)		Avg Monthly Level
VARIABLES	All	SME	Large	All
Post x M&A	-0.021**	-0.022**	-0.007	-0.045***
	[0.009]	[0.009]	[0.068]	[0.006]
Observations	792,542	776,962	15,103	765,955
R-squared	0.132	0.131	0.301	0.165
Industry-Location-Size-Time FE	YES	YES	YES	YES
Bank FE	YES	YES	YES	NO
Bank Controls	YES	YES	YES	YES
Firm Controls	YES	YES	YES	YES

Notes: This table is analogous to the first four columns of Table VII. In columns (1)–(3), it is defined as the difference between the log of NPL between November 2009 and November 2007 for the pre period and between November 2011 and November 2009 for the post period. In column (4) we consider an alternative definition, as given by the log of the average NPL over every month of the pre-event period and over every month of the period spanning between the announcement of the merger and November 2011 for the post period. The main difference is that we use the full sample of firms and both the pre and the post period relationships, so that the number of observations is the same as in Table V, columns (1)–(4). With industry-location-size-time fixed effects, splitting the full sample of firms in column (1) into SME and Large firms gives rise to additional singletons that we exclude from our regressions; thus, the sum of the observations in columns (2) and (3) does not equal the observations in column (1). One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level. For additional information on the construction of these variables, see the data appendix (in Appendix A).

Table B.VIII: NPL spillover

	NPL of Banks Outside the Restructuring Program					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	All	Exposed Firms	Non-Exposed Firms	All	Exposed Firms	Non-Exposed Firms
Loan Application Rejected by M&A Bank	-0.009	-0.024	-0.001			
	[0.017]	[0.026]	[0.024]			
Loan Application Rejected by M&A or SIP Bank				-0.009	-0.022	0.006
				[0.017]	[0.021]	[0.031]
Observations	13,823	7,425	5,619	13,823	10,404	2,777
R-squared	0.127	0.149	0.191	0.127	0.142	0.239
Industry-Location-Size FE	YES	YES	YES	YES	YES	YES
Average Bank Controls	YES	YES	YES	YES	YES	YES
Firm Controls	YES	YES	YES	YES	YES	YES

Notes: We study the performance of loans granted by all commercial and cooperative banks and the few savings banks that did not participate in a SIP or a M&A, to firms with loan applications rejected by any of the savings banks that did a M&A (columns (1)–(3)) and a M&A or a SIP (columns (4)–(6)). The analysis is conducted at the firm level. Hence, the dependent variable in columns (1)–(6) is a dummy variable that is equal to one when a loan of firm i is non-performing in November 2011 (conditional on being performing on November 2009). The explanatory variable in columns (1)–(3) is a dummy variable that is equal to one if firm i applied for a loan to one or more savings banks that did a M&A and this application was rejected in the post period (November 2009–November 2011). In columns (4)–(6), instead, the dependent variable is a dummy that equals one if firm i applied for a loan to one or more savings banks that did a M&A or a SIP and this application was rejected in the post period (November 2009–November 2011). The set of firm-level control variables we use are the same as in Table V, moreover we add industry-location-size fixed-effects and the average characteristics of the banks that do not participate in the consolidation process between November 2009 and November 2011, and to which firm i is exposed. In columns (1) (resp., (4)) we use all firms that applied for a loan to one or more savings banks that did a M&A (resp., a M&A or a SIP). In columns (2) (resp., (5)) we further restrict the sample to those firms that in November 2009 had a positive credit balance in the savings banks that did a M&A (resp., a M&A or a SIP), and in columns (3) (resp., (6)) we use only the firms with no credit exposure to M&A banks (resp., M&A or SIP banks). With industry-location-size fixed effects, splitting the full sample of firms in column (1) (resp., (4)) into Exposed and Non-Exposed firms gives rise to additional singletons that we exclude from our regressions; thus, the sum of the observations in columns (2) and (3) (resp., (5) and (6)) does not equal the observations in column (1) (resp., (4)). Robust standard errors (in brackets) are clustered at firm level. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level. For additional information on the construction of all the variables, see Appendix A.

Table B.IX: Marginal cost estimation results

VARIABLES	
Loan Volume	0.020***
	[0.003]
Log of Total Assets	-0.072***
	[0.008]
Bank FE	Yes
Observations	1,632
R-squared	0.513

Notes: Standard errors in brackets are clustered at the bank level. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level. An observation is a bank-month. Loan Volume are expressed in BE.

C. For Online Publication – Construction of the CoVar regression

We measure the marginal contribution of each credit institution to the risk of the system based on the CoVaR (i.e., the value at risk (VaR) of the financial system conditional on an institution being under distress) of Adrian and Brunnermeier (2016). This measure relies on the growth rate of the market value of total financial assets, which is defined as the growth rate of the product of the market value of a given institution i and its ratio of total assets to book equity. However, the shares of the savings banks involved in the consolidation program of the Spanish banking system over the period 2009–2011 were not listed. For this reason, we estimate a type of CoVaR measure based on bonds issued by Spanish banks. These issuances are collected in a proprietary dataset at the Banco de España.[28] Thus, we adapt the CoVaR to measure the sensitivity of a representative Spanish banking system bond yield to the increase of the bonds yields of each specific credit institution. We first use quantile regressions at the percentiles 50 and 90 to estimate the following equations using weekly data:[29]

$$X_t^j = \alpha^j + \gamma^j M_{t-1} + \varepsilon_t^j \tag{C.1}$$

$$X_t^{system} = \alpha^{system|j} + \beta^{system|j} X_t^j + \gamma^{system|j} M_{t-1} + \varepsilon_t^{system|j} \tag{C.2}$$

where X_t^j is the percentage change of institution j average bond yield which is obtained as a weighted average of the yields at a given week t of all individual outstanding bonds issued by istitution j.[30] X_t^{system} is the percentage change of the bond index yield. This yield is just the equally weighted average of the average of yields of all institutions excluding institution j. We consider two alternative measures of the system bond yield. First, we consider the average yield obtained from the the bonds issued by the savings banks used in our previous analyses. Second, we consider the average yield of a wider sample of banks, which consists of all Spanish banks with outstanding bonds during the period November 2007–November 2011. M_{t-1} is a set of state variables that includes the VIX, the percentage change in one-year Spanish sovereign bond, the spread of 12-month Euribor over 1-year sovereign bond, the slope (10-year minus 1-year sovereign bonds), and the differential of 10-year BBB corporate bond

[28]We verify that all securities in Dealogic are part of our sample, which in addition contains some others that are not in Dealogic. The sample of bonds used to estimate the CoVaR consists of those securities for which we have information on their yields in Datastream. This information is available for 32 out of 37 credit institutions that are used in our sample. In total, we use information on 372 senior unsecured bonds for which daily yields are available. Moreover, for some tests, we extend our sample with the issuances of 13 additional Spanish banks and savings banks.

[29]The 90th percentile is associated to a higher risk than that of the 50th percentile, given that the higher the increase in bond yields, the higher the increase in the risk of that bond.

[30]With a slight abuse of notation, in this section, depending on whether a bank participated in an operation of consolidation, we denote by j either a bank group (M&A or SIP) or an individual (commercial, savings) bank.

index minus 10-year sovereign bond.

We replace the coefficients obtained from equations (C.1) and (C.2) using quantile regressions, in the following equations to obtain VaR and CoVaR at level $q\%$ as follows:

$$\begin{aligned} \text{VaR}_t^j(q) &= \widehat{\alpha}_q^j + \widehat{\gamma}_q^j M_{t-1} && \text{(C.3)} \\ \text{CoVaR}_t^j(q) &= \widehat{\alpha}_q^{system|j} + \widehat{\beta}_q^{system|j}\text{VaR}_t^j(q) + \widehat{\gamma}_q^{system|j} M_{t-1} && \text{(C.4)} \end{aligned}$$

Then, we obtain the marginal contribution of a given institution j to the overall risk of the system, which is denoted by ΔCoVaR_t^j, as the difference between CoVaR_t^j conditional on the distress of institution j (i.e., q=0.9) and the CoVaR_j of the "normal" state of that institution (i.e., q=0.5):

$$\Delta\text{CoVaR}_t^j(90\%) = \text{CoVaR}_t^j(90\%) - \text{CoVaR}_t^j(50\%) \tag{C.5}$$

The CoVaR is estimated on a weekly basis and we convert it to a monthly frequency by taking the maximum of the weekly CoVaRs within a given month. After estimating the monthly $\Delta\text{CoVaR}_t^j(90\%)$ for each institution, we perform a regression analysis in which the dependent variable is the ΔCoVaR of a given institution j in a given month t ($\Delta\text{CoVaR}_t^j(90\%)$) and regress it on the ratio of NPL of institution j plus a series of individual bank (X_{jt}) and global (W_t) control variables:

$$\Delta\text{CoVaR}_t^j(90\%) = \alpha_j + \beta\text{NPL}_{jt-1} + \delta X_{jt-1} + \eta W_{t-1} + \varepsilon_{jt} \tag{C.6}$$

where α_j denotes the use of bank fixed effects and X_{jt} refers to the use of monthly bank characteristics such as size (logarithm of total assets), leverage (total liabilities over total assets), risk (ratio of NPL), liquidity (credit over deposits), profitability (ROA), and FROB funds made available to each bank (relative to total assets). The set of global control variables includes: VIX index, (log) changes in Spanish and European bank bond indices and Spanish banks average bond yield.