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

Sergio Mayordomo
Banco de España

Nicola Pavanini
Tilburg University & CEPR

Emanuele Tarantino
Luiss University, EIEF & CEPR

December 2021

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. Compared to bank business groups, we find that bank mergers' market power produces a contraction in credit supply, higher interest rates, but also a reduction in non-performing loans. We then estimate a structural model of credit demand and supply. Through counterfactuals, we quantify cost efficiencies and improvements in financial stability that consolidation should deliver, in order to outweigh welfare losses from reduced credit supply.

*We are grateful to Roberto Blanco, Fabio Castiglionesi, Giacinta Cestone, Francesco Decarolis, Andreea Enache, Isil Erel, Xavier Freixas, Àngel Gavilán, Mariassunta Giannetti, Luigi Guiso, Tomohiro Hirano, Jakub Kastl, Francine Lafontaine, Jack Liebersohn, Marco Pagano, Ariel Pakes, Daniel Paravisini, José-Luis Peydró, Andrea Polo, Andrea Pozzi, Mar Reguant, Oliver Rehbein, Fabiano Schivardi, Gloria Sheu, Michelle Sovinsky, Steve Tadelis, Elu von-Thadden, and Carlos Thomas. We also thank conference and seminar participants at the Banco de España, Bocconi, CEPR Virtual IO Seminar Series, CEU (Budapest), EIEF, European Commission, FDIC, HSE (Moscow), IBEFA meetings, LUISS, NBER Summer Institute IO meetings, SKEMA, University of Zürich, and UPF. The views expressed are those of the authors and do not necessarily reflect those of the Banco de España or the Eurosystem.

1. Introduction

In banking systems featuring many undiversified banks, fierce competition can give rise to excessive risk taking. If bad risks then translate into problematic loans, public intervention drawing on government funds 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. This happened in Europe, where, during the last decade, 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 (Granja, Matvos and Seru, 2017; Allen, Clark, Hickman, and Richert, 2019).

Financial regulators' case for bank mergers is supported by the presumption that consolidation makes troubled institutions more capable to absorb losses. The literature has shown that, after a merger, banks restrict their credit supply, especially at the expense of small and medium firms (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). It has also been shown that these costs could be compensated by the efficiencies produced by consolidation (Houston, James and Ryngaert, 2001; Focarelli and Panetta, 2003; Panetta, Schivardi and Shum, 2009; Erel, 2011), or by mergers' propensity to mitigate financial shocks' propagation (Petersen and Rajan, 1995; Scharfstein and Sunderam, 2016; Favara and Giannetti, 2017; Giannetti and Saidi, 2019). However, the academic literature, and most regulators alike, have not considered alternative bank integration modes,[1] and how consolidation affects financial stability. This is unfortunate, especially because of the costs that banks' consolidation programs have for taxpayers.

We study how alternative forms of bank consolidation, namely traditional mergers and business groups, differentially balance the benefits and costs of integration for credit supply and financial stability. In bank business groups, 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

[1]In the telecommunications or pharmaceutical industries, antitrust agencies have allowed firms to engage in network sharing agreements or research joint ventures instead of full-fledged mergers.

install information processing technologies that would not be feasible absent the deal. At the same time, business groups are less likely to give rise to market power than mergers, due to their decentralized structure. The risk management unit generates information on borrowers' credit merit, but the use of that information may well differ across legally independent banks depending on loan officers' incentives (Stein, 2002). This makes coordination of lending policies, and thus the exercise of market power, more difficult than in a full-fledged merger.

We empirically document a novel trade-off. On the one hand, compared to business groups, we find that M&A reduce credit supply and increase interest rate spreads. On the other hand, they significantly reduce the amount of non-performing loans (NPL) in the economy, the loans extended to risky firms and the risk of bank default. These results are explained by the differential market power effect exerted by M&A compared to business groups, and not by differences in the efficiency gains produced by the two consolidation modes. Market power produces a restriction in credit supply. However, if competition pushed banks to extend credit to high-risk borrowers before consolidation, the marginal borrower is likely to be worse than the inframarginal ones. As a consequence, reducing credit improves the selection of borrowers. We also quantify the welfare effects of the program by means of a structural model that builds on the recent literature applying equilibrium frameworks from empirical industrial organization to financial markets (Egan, Hortaçsu and Matvos, 2017; Crawford, Pavanini and Schivardi, 2018).

To obtain these results, we study the Spanish savings banks 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 witnessed by the hoarding of credit to the construction sector that ultimately led to a NPL problem. 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, the program led to a consolidation wave by which the number of savings banks went from 37 to 12. In practice, all savings banks participated in an operation of consolidation. The asset value of the institutions involved 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]

The Spanish consolidation program is an ideal lab to answer our research

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

question. The first advantage of studying the Spanish program is that savings banks could choose to integrate doing a standard M&A or a business group. We can then compare the relative impact of the two consolidation modes on the supply and performance of credit, and on the stability of the banking system. The crucial difference between M&A and business group banks is that the latter remained stand-alone legal entities: they kept their pre-consolidation brands, and continued reporting their credit operations independently to the credit registry. This makes the organizational structure of a business group less centralized than in a M&A. Moreover, our reconstruction of how the program unfolded documents that the banks' choice between M&A and business group was driven by political considerations. Specifically, regional public authorities sitting in savings banks' governing bodies favored consolidation via M&A with savings banks in the same region, in order to avoid losing control of the merged entity.

The second advantage is that the Banco de España Central Credit Registry gives us access to comprehensive data that can be used to identify the effects of interest on credit supply and financial stability. We have access to information on outstanding amount of firm credit with each bank at the monthly level. The volume of NPL reported by banks is at the firm-month level. The information on the interest rate applied by banks to newly issued loans is aggregated at the bank-month level. We also have information on the requests for information made by banks regarding the credit situation of new borrowers in the credit registry. The final dataset we use for estimation has 511,263 firm-bank relationships and 367,676 non-financial corporations between November 2007 and November 2011. We stop in November 2011 because during the next semester Spain received rescue packages to cope with the European sovereign debt crisis.

We first provide a descriptive analysis of M&A and business group banks before consolidation. We show that there is no evidence of assortative matching between banks in the two groups. Specifically, before consolidation, M&A and business group banks were comparable with respect to balance sheet characteristics and business model. We also find no evidence that the choice of consolidation mode was driven by market shares' overlap at the local level. Our tests, instead, show that the choice between M&A and business group was driven by regional politics. We use data on credit concentration from the 1990s, a few years after a lift on a regulation that limited banks' possibility to open new branches. We find that M&A between 2009 and 2010 happened disproportionally more between savings banks headquartered within their main area of influence in the 1990s. This is consistent with regional governments' will to avoid M&A happening across regions.

Post consolidation, we use data on branches to show that M&A and business group banks are similar in terms of the efficiency gains they produce. We then use the dataset on banks' requests for information to show that, compared to business groups, M&A banks have a stronger propensity to use hard information to assess borrowers' credit merits. This is consistent with Stein's (2002) conjecture that loan officers in more centralized organizations, like M&A bank groups, are more likely to use hard information when deciding to extend a loan. Finally, we present two tests whose results confirm that there is limited coordination in the credit policies within business groups. We start by using data on requests for information submitted by the savings banks in the same business group and regarding the same borrower. We show that business group banks treat a loan application submitted by this borrower differently with respect to the average savings bank in the same group. We then present evidence of borrower poaching between savings banks within the same business group.

To develop our testable predictions on the impact of market power on credit supply and performance, we propose a stylized model of credit with selection building on Einav and Finkelstein (2011). This setting allows us to 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 cost schedules. We instead interpret the merger as a situation in which banks have market power. In this framework, moving from a competitive allocation to an allocation with market power causes a restriction in credit supply but also an improvement in borrowers' selection (as captured by lower costs). The reason is that the marginal borrower is worse than the inframarginal ones. A challenge to the identification of this trade-off is that, if the merger were to independently produce cost efficiencies, one should also expect a further reduction in savings banks' costs. Thus, to identify the effect of market power, we need a comparison group featuring little, or no market power and a comparable change in costs post consolidation. Our descriptive analysis above shows that the sample of savings banks doing a business group fulfills these requirements.

In our reduced-form analysis, we start by studying the differential effect of M&A and business groups on credit supply. After consolidation, the credit balance of a given firm dealing with a M&A bank fell by about 3% when compared to that of a similar firm dealing with a business group bank, or about 12,600 euro per firm per semester. 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. We also find that a loan granted by a M&A bank is 42 basis points (bp) more expensive than that granted by a business group bank. 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 business groups on financial stability, we look at performance and composition of loan portfolios, and bank default risk. We find that M&A banks report less NPL than business group banks.[3] Specifically, the share of firm credit that, after consolidation, turns out to be non performing is about 1 percentage point (pp) less for M&A banks than for business group banks. For these results, we exploit variation coming from borrowers with the same size and the same period, SIC-3 industry, and province. In this analysis, we focus on firm-savings bank pairs featuring no credit relationship at the consolidation date. We do this to be sure that loan refinancing, or ever-greening, does not impair the interpretation of our results.

When studying loan portfolio composition, 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 result helps to explain the smaller proportion of NPL reported by M&A banks post consolidation. We conclude the analysis of the relative effects of consolidation modes on financial stability with two additional results. The first is that, post consolidation, M&A banks' risk of default decreases when compared to that of business group banks. The second is that the reduction in the NPL reported by the savings banks that participated in the program did not cause an increase in the NPL of the banks outside the program.

Overall, we show that the credit supply contraction produced by M&A banks' market power comes with an improvement in the selection of borrowers and in the stability of the banking system. Our results are not explained by differences between M&A and business group banks in the baseline, nor by differences in the efficiency gains generated by each consolidation mode. Instead, we can relate them to the differences in the use of information and coordination of credit policies across consolidation modes. While we obtain our findings by comparing M&A and business group banks, we find similar results when separately comparing M&A

[3] We use NPL to proxy the the impact of consolidation on borrower selection. NPL also have an effect on financial stability. We 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.

and business groups to commercial banks in terms of credit supply and NPL accumulation.

To conclude, we quantify the impact of the consolidation program 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.[4] 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.[5] 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' average costs increase in the quantity of credit, which is consistent with banks' marginal borrower being riskier than the infra-marginal ones in the benchmark.

In our counterfactual analysis, 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. For the long-run counterfactual, we quantify the reduction in average 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 by a 0.06% reduction in average costs, corresponding to 5.4% of its standard deviation, or by a 1.13 percentage points drop in banks' default risk, about half of its standard deviation. By doing this, we simulate what antitrust authorities could do to screen anticompetitive bank mergers.

The consolidation program came at a time in which Spain was suffering an economic downturn, and banks had accumulated relatively large proportions of NPL. One may wonder why an analysis of such a time period informs the effects of consolidation in potentially more stable periods. The answer is that bank

[4] We model interest-rate competition at the bank-month level, which corresponds to the level of aggregation of interest-rate information in our data. Using aggregate bank-time level interest rates as opposed to borrower level ones, when the latter data is not available, is common practice among papers estimating structural models of demand for loans (Aguirregabiria, Clark, Wang 2020; Wang, Whited, Wu, Xiao 2020).

[5] 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).

consolidation programs are typically decided by governments and regulators in times of crisis, as a response to the problems of ailing banks. On top of the examples above, we here add the case of Japan, where after the NPL crisis of the late 1990s, the government injected public capital into the banking sector and advised banks to merge (Hoshi and Kashyap, 2004). In this respect, our analysis is of interest in light of the probable consequences that the COVID-19 crisis may have for the banking sectors around the globe. It is also useful to remark that bank business groups are not a peculiarity of the Spanish banking system. Other examples of bank business groups organized likewise are the German *Sparkasse* or the Italian *Banche di Credito Cooperativo*.

On top of the literature on consolidation in banking, discussed above, we contribute to several other strands of the literature. The trade-off between competition and stability in banking has been a contentious subject for many years (see Vives (2016) for an exhaustive survey), and the controversy has not been conclusive to date. Vives (2016) points out that the trade-off arises because of regulatory imperfections, or outright regulatory failure. Instead, the relevant question should be what can be done to reduce the conflict. We embrace this approach to analyze the case of bank consolidation. We are the first to document how different consolidation modes affect the trade-off between market power and stability in banking, and then take a normative approach. Specifically, we use our structural model to analyze how financial stability considerations related to the impact of consolidation on banks' risk of default and bank efficiency can be incorporated into competition authorities' merger review process.

Our structural model makes two contributions to the empirical industrial organization literature that studies financial markets (see Clark, Houde and Kastl (2021) for a review). First, on top of banks' pricing competition, we also model banks' decision to reject borrowers above a threshold of expected default risk. This introduces choice-set heterogeneity across borrowers based on their degree of risk, in the spirit 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 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 (other things equal).

We also contribute to the 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, 2014). Relative to this body of empirical work, we are the first to provide evidence of the effect of a country-wide bank consolidation program on borrowers' selection.

Finally, our empirical analysis comparing M&A and business groups allows us to show how the organization of consolidation affects economic outcomes. In this literature, Gugler and Siebert (2007) compare mergers and research joint ventures in the semiconductor industry; Braguinsky, Ohyama, Okazaki, and Syverson (2015) study how changes in ownership affect the productivity and profitability of producers; Eliason, Heebsh, McDevitt, and Roberts (2020) consider how acquisitions affect firm behavior and performance in the dialysis industry. On top of establishing the main effects of interest, our dataset allows us to perform an in-depth investigation relating differences across consolidation modes in the use of information and coordination of credit policies to the exercise of market power.

2. The savings banks' sector consolidation program

In this section, we describe the savings banks' sector consolidation program. We also present a conceptual framework to illustrate our testable hypotheses and introduce the empirical strategy.

2.1. Background facts

In the aftermath of the financial crisis that hit the country in 2008, the Spanish government enacted the Royal Decree 9/2009 (*Real Decreto-Ley 9/2009*) of 26 June 2009 (the Law from now on) to restructure the sector of Spanish savings banks (*cajas de ahorros*). At the time, savings banks' assets represented about 40% of Spanish banking assets (European Commission, 2017). As in other countries, these banks played an important role supporting the economic development of local areas, in a context featuring a high representation of regional public authorities into their governing bodies.

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 led savings banks to take poor investment choices. As of 2010, the sector was 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 dependent on the wholesale funding sector.

To address these issues, the Spanish government did two things. First, it gave 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.[6] 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).[7] In practice, 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. Second, the Law reformed the corporate governance of 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 key 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 institucionales de protección* (SIP). Since the program targeted the sector of savings banks, no such bank consolidated with a commercial or a cooperative bank in the period under consideration. In Section 4.1, we will show that SIP and M&A banks were statistically comparable in terms of financial characteristics, business model and overlap at local level before consolidation. In Section 4.2, we will analyze M&A and SIP banks after they consolidated. For the purposes of this section, it is useful to remark that SIP are a form of business group. Their structure had to conform to the prescriptions of the Law, and was thus uniform across groups, and across provinces within groups. SIP feature similarities and one crucial difference with respect to standard M&A. We start with the former. First, in analogy to M&A, SIP banks were required to establish pacts of full mutual assistance on liquidity and solvency, and were responsible on a consolidated basis for the fulfillment of regulatory requirements. Second, the Law required that

[6] Savings banks were asked to submit a plan with details on the consolidation plan in exchange of the capital subscription by FROB. The consolidated entity had to commit to buy-back this capital from FROB as soon as possible.

[7] Table B-I (Appendix A.2) reports the list of the operations of consolidation (SIP and M&A) that took place during this period, which are those we consider in our empirical analysis.

SIP last at least ten years. Finally, like M&A banks, SIP banks had access to consolidated information on the firms interacting with other savings banks in the same group, so did 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 means that they kept their pre-consolidation brands, and continued reporting their credit operations independently to the credit registry. This makes the organizational structure of a SIP less centralized than that resulting from 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 reflects what happens within M&A banks. SIP banks' legal independence is likely to impair coordination of credit policies, due to the possibly different use of the credit-merit analyses produced by the risk management unit depending on loan officers' incentives (in Section 4.2, we report evidence consistent with this intuition). Since coordination of supply is fundamental for the exercise of market power, we then conjecture that the market power effect is stronger for M&A.

We now describe how the consolidation program unfolded. The choice between M&A and SIP was critically influenced by considerations related to regional politics. 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 savings banks to form a SIP (Banco de España, 2017). SIP allowed savings banks to consolidate and at the same time preserve legal independence. As we will show in Section 4.1, despite all M&A happened between banks with headquarters within the same region, and all SIP happened between banks with headquarters in different regions, they are comparable in terms of overlap at the province level (which is the relevant market size for antitrust purposes) and other financial and economic characteristics.

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.[8] We also introduce our empirical strategy.

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 in 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. That is, an increase in q comes with a higher marginal cost and a lower profit margin.[9] More formally, the MC and AC schedules slope upward, $MC'(q), AC'(q) > 0$, which gives rise to advantageous selection.[10] Moreover, since $C(q)$ is convex, $MC(q) > AC(q)$ for all $q \in [0, 1]$.

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.

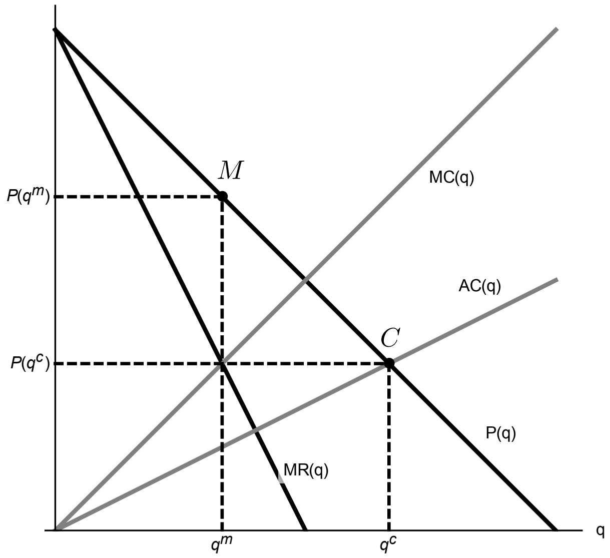
We then conjecture that the M&A wave brings the economy closer to the monopolistic outcome. The monopoly allocation (M in Figure 1) is given by the value of q such that $MR(q^m) = MC(q^m)$, where $MR(\cdot)$ denotes the marginal revenue curve. It comes with lower supply of credit than with perfect competition,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

[8] 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, banks reject a firm based on its observable degree of risk.

[9] 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.

[10] 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 average 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



by banks.

This simple setup delivers the following trade-off: on the one hand, M&A's market power 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. A challenge to identification of the effects of market power is that, if consolidation were to independently produce cost efficiencies, one should also expect a further reduction in AC and MC for any given q. Thus, we need a comparison group featuring little, or no market power and a comparable change in costs post consolidation. This group is the sample of SIP banks. We will show in Section 4.2 that M&A and SIP banks are comparable in terms of the efficiency gains they produce over the sample period we consider. We will also show evidence of uncoordinated credit policies, and poaching between banks within the same SIP.

In the reduced form analysis we then estimate the differential impact of M&A and SIP on q, $P(q)$ and costs (proxied by NPL). By doing so, we effectively quantify the effects produced by M&A's stronger market power on our outcome variables, controlling for consolidation-related efficiencies. In the structural analysis, we use our model to quantify the welfare effects of the consolidation program.

3. Data and descriptive statistics

Our main data source is the Banco de España Central Credit Registry, 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. One limitation of loan interest-rate information is that, different from outstanding credit, it is only available at bank-month level, with the possibility of distinguishing between distinct classes of loan size and maturity. We also have data on the volume of NPL reported by banks in relation to a given firm, but cannot identify the firm's specific loan that then turns out to be problematic. An additional dataset we use contains all the requests for information made by banks on firms' credit situation to the Spanish credit registry. Banks submit these requests when they receive a loan application from a new borrower. Such requests for information enable us to identify firms that are seeking a bank loan. Finally, we use firm and bank balance-sheet information collected by the Banco de España in its role as a supervisory authority.

In what follows, we denote by j the group of savings banks that do a M&A or a SIP. The savings banks that participate in 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 registry until the end of our sample period. As a consequence, after consolidation, 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). Before consolidation, we aggregate the information on the savings banks that will later be part of M&A or SIP. More information on the construction of the dataset is available in Appendix A.1.

3.1. Banks, firms and lending relationships

Panel A of Table I reports the value of some key bank characteristics over the sample period. As we do in our regression analysis, the information is aggregated at the bank group level. Confirming the high exposure to the real estate and the construction sectors, we see that savings banks extended credit accounting for about one-third of the value of their assets to these two sectors only. The ratio of NPL over total credit is equal to about 3.5% on average, but there is large heterogeneity across bank groups. Panel B reports information on firm characteristics during the sample period. It 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).

Table I: Summary statistics

Panel A: Bank groups						
VARIABLES	November 2007–November 2011					
	Mean	Median	Standard Deviation	5th Percentile	95th Percentile	N
TA (BE)	83.10	47.70	83.40	19.70	280.00	60
Capital Ratio (%)	5.60	4.94	1.71	3.67	8.88	60
Credit/Deposits	1.82	1.81	0.31	1.29	2.38	60
ROA (%)	0.42	0.45	0.28	0.05	0.79	60
NPL (%)	3.41	3.16	2.74	0.45	8.68	60
(Credit to RE and Construction)/TA (%)	28.24	29.50	5.73	17.59	35.58	60
Panel B: Firms						
VARIABLES	November 2007–November 2011					
	Mean	Median	Standard Deviation	5th Percentile	95th Percentile	N
TA (ME)	1.92	0.48	5.47	0.04	7.03	1,011,679
Total Liabilities/TA (%)	72.77	79.87	73.81	19.41	100.00	1,011,679
Liquid Assets/TA (%)	9.21	3.28	14.64	0.00	40.98	1,011,679
ROA (%)	3.99	5.15	18.49	-23.71	27.52	1,011,679
Panel C: Bank-Firm Relationships						
VARIABLES	November 2007–Consolidation date					
	Mean	Median	Standard Deviation	5th Percentile	95th Percentile	N
ΔLog(Credit)	-0.04	-0.02	1.34	-2.24	2.60	1,634,100
NPL (%)	1.83	0.00	13.10	0.00	0.00	1,634,100
Interest rate spread (%)	1.81	1.61	0.87	0.67	3.39	354
Panel D: Bank-Firm Relationships						
VARIABLES	Consolidation date–November 2011					
	Mean	Median	Standard Deviation	5th Percentile	95th Percentile	N
ΔLog(Credit)	-0.13	-0.04	1.16	-2.20	0.97	929,625
NPL (%)	3.11	0.00	17.08	0.00	0.00	929,625
Interest rate spread (%)	2.73	2.78	0.58	1.71	3.56	234

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 each individual group j, Panel B at the level of individual firms, Panels C and D are at the bank-firm level for credit change and NPL, and at the bank-month level for interest rate spreads. 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 for the period between November 2007 and November 2011. Panel C reports descriptive statistics (at the semiannual basis) on the change in the credit balance between November 2007 and the date in which consolidation took place, on the ratio of NPL over total loans for the whole sample of firm-bank pairs, and on the average interest rate spread over the three-month Euribor at the bank-month level. Panel D does the same for the period between the date of consolidation and November 2011. For additional information on the construction of these variables, see Appendix A.1.

In Panels C and D, we report information on NPL and credit change aggregated at the bank-firm level before consolidation (Panel C) and after consolidation (Panel

D). These are the same bank-firm relationships we use in our main regressions. The information on interest rate spreads is at the bank level. We see that 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 between the first and the second period. Our goal is to estimate the differential change in these variables across M&A and SIP post consolidation.

3.2. The systemic impact of NPL

We use NPL to proxy the relative effects of M&A and SIP on banks' costs, which capture banks' selection of borrowers in the setting of Section 2.2. To show 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.[11] The CoVaR we obtain then 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 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.

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 increases the contribution of this bank to the risk of the system by 0.13 pp. This represents 24% 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

[11] 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 rely on information on bond yields. Appendix A.3 describes the CoVaR methodology and how we implement it.

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

VARIABLES	(1) ΔCoVaR Mergers	(2) ΔCoVaR All	(3) ΔCoVaR All
NPL	0.034***	0.049***	0.059***
	[0.011]	[0.008]	[0.006]
Observations	519	519	1,052
R-squared	0.505	0.562	0.642
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, and (FROB funds)/TA (for information on the construction of these variables, see the data appendix (in Appendix A.1)). 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 A.3 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 A.3.

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 sample period goes from November 2007 to November 2011. The dataset comprises information on a total of 511,263 firm-bank relationships and 367,676 non-financial corporations (354,470 in the pre-event period and 267,355 in the post period). We consider the savings banks that participated in one of the 12 M&A or SIP between November 2009 and December 2010, which account for about 40% of the total credit in the economy and 90% of the total credit in the savings banks' sector (the list is in Table B-I, in Appendix A.2). We then trace the effects of these consolidations up to November 2011. We stop in November 2011 because during the next semester Spain received rescue packages to cope with the European sovereign debt crisis.

4.1. Comparability of M&A and SIP banks *before* consolidation

In this section, we first show that the decision to do a M&A, as opposed to a SIP, is not correlated with province-level overlap in November 2009, and confirm instead that regional politics played a crucial role in determining the choice of consolidation mode. 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. Finally, we show that the common trend property is satisfied by our main outcome variables in the period before consolidation.

4.1.1. 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 study whether local market overlap explains the decision to do M&A or 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, we compare M&A and SIP banks geographical overlap at the province level before consolidation.

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 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:[12]

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

We find that the choice to do a M&A between November 2009 and December 2010 is not correlated with province-level overlap in November 2009 (column (1)). Importantly for our empirical strategy, province-level overlap before consolidation does not seem to explain the specific consolidation mode chosen by banks.

[12] Using the market share of the smallest savings bank in a given group (M&A or SIP) would bias downward the measure of overlap. For example, if there are three savings banks, the third bank may have a very small market share relative to the others and yet there would be overlap between the largest two in the province.

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

	(1)	(2)
VARIABLES	November 2009	January 1995
Credit overlap	0.676	2.887**
	[1.087]	[1.403]
Observations	600	600
R-squared	0.268	0.323
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 and a measure 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, Credit/Deposits, ROA, 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.1.

In column (2), we compare province-level overlap between M&A and SIP banks using information from January 1995, which is the first month in which credit information is available in the Spanish credit registry. 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). Location in 1995 then captures savings banks' proximity to their main area of influence, or headquarter.

The coefficient in column (2) is not only statistically significant, but also economically larger than the coefficient in column (1). That is, savings banks with larger market overlap in their area of influence in 1995 are disproportionally more likely to do a M&A between November 2009 and December 2010. This result is consistent with regional governments' will to avoid M&A happening across regions, confirming that regional politics was a crucial driver behind the choice of consolidation mode.

4.1.2. Financial and economic characteristics

In Table IV, we compare M&A and SIP banks' financial and economic characteristics as of December 2008.[13] 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 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 in 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 in the values of the variables for M&A and SIP banks.

We find that there is no systematic evidence of assortative matching between M&A and SIP banks based on observable financial or economic characteristics. Except for total assets, which tend to be larger for M&A banks (but the difference is not statistically significant), the two groups feature comparable values across the variables we consider, including bank capital.[14] The fact that the two groups are balanced with respect to the values of NPL over total loans and the exposure to the real estate and construction sectors suggests that these banks were comparable in the extent to which they extended crony lending. Since not all of the consolidations 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. There is also no evidence of significant differences in the ratio of credit over deposits, which means that M&A and SIP banks featured similar business models before the program started.

Panel D shows that there is no statistically significant difference between the standard deviation of M&A and SIP banks' characteristics. This means that if "good" banks consolidate with "bad" banks on margins like capitalization, NPL over total loans, or profitability, or big banks consolidate with smaller banks in terms of total assets, this pattern is not different between M&A and SIP banks.

Finally, we checked that M&A and SIP banks were balanced in terms of the risk perceived by their investors. 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 average bond yield was 4.9% for M&A banks

[13] We use this month because it is the last for which end-of-year information is available before the first operation of consolidation takes place (in November 2009).

[14] 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	
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)
(FROB funds)/TA (%)	1.016	1.115	-0.099	1.115	1.016	0.099
			(0.528)			(0.528)
NPL (%)	3.720	3.151	0.205	3.825	3.553	0.272
			(0.523)			(0.648)
(Credit to RE and Construction)/TA (%)	28.761	31.562	-2.801	28.592	30.737	-2.145
			(3.105)			(3.028)
	Panel C: Main Bank			Panel D: Standard Deviation		
VARIABLES	Means		Difference	Means		Difference
	M&A	SIP		M&A	SIP	
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	2.044	-0.040	0.264	0.270	-0.006
			(0.219)			(0.098)
(FROB funds)/TA (%)	1.115	1.016	0.099	-	-	-
			(0.528)			-
NPL (%)	4.446	4.991	-0.534	0.596	1.476	-0.880
			(0.820)			(0.596)
(Credit to RE and Construction)/TA (%)	26.556	25.195	1.361	4.345	11.010	6.665**
			(8.544)			(2.398)

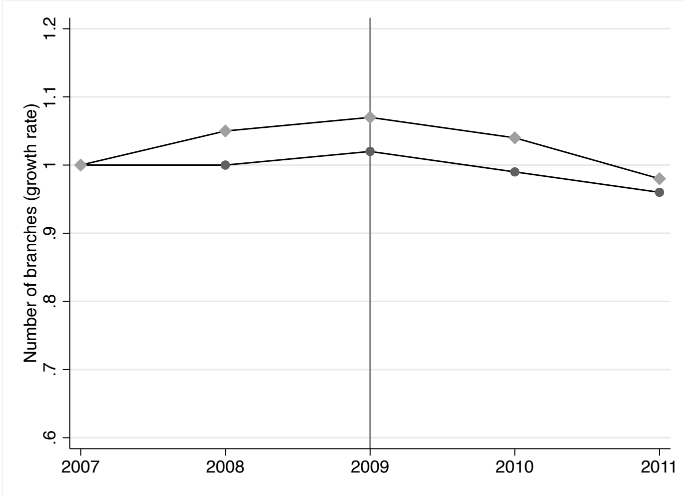
Notes: This table reports bank characteristics for M&A banks and SIP banks in December 2008 (i.e., one year before the bank consolidation process started). All the variables are in percentages, excluding total assets, which are in billions of euros, and the ratio of credit over deposits. In Panel A we 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 bank groups 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 savings 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 of bank characteristics across the groups of banks, with the values in brackets reporting robust standard errors associated with a mean test. 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.1.

and 5.1% for SIP banks).

4.2. M&A and SIP banks *after* consolidation

In this section, we analyze M&A and SIP banks after consolidation. We will show that M&A and SIP banks generate comparable efficiency gains in the post period. We then document that M&A banks are more likely to use hard information when processing a loan application. Finally, we report evidence consistent with lack of coordination in the usage of information and in the actual supply of credit within SIP.

Figure 2: Efficiency gains



Notes: The figure reports the growth rate of the number of branches at the yearly level between 2007 and 2011 (2007 is the base year) separately for M&A banks (grey line) and SIP banks (black line). Since the information is aggregated at the group-level (M&A or SIP), we do not report the confidence intervals.

4.2.1. Efficiency gains

A condition for the identification of the impact of market power on the supply and performance of credit requires that M&A and SIP banks are on similar cost curves post consolidation (Section 2.2). For this to be the case, we should not observe a large differential pattern in the efficiency gains produced by M&A and SIP post consolidation. This would be consistent with the Spanish regulator's requirement that SIP generate the same efficiencies as M&A.[15]

In Figure 2, we report evidence in line with this requirement based on the pattern of the number of banks' branches, which is a standard proxy for efficiency gains in the literature on bank mergers (Focarelli and Panetta, 2003). Specifically, we obtained from the Banco de España yearly information on the number of branches between 2007 and 2011 for the savings banks participating in an operation of consolidation. The figure reports the growth rate in the number of branches separately for M&A and SIP banks, taking 2007 as base year. It shows that, for both groups, the branches increased before the Law was passed in November 2009, and started descending at a comparable pace in the post period.

[15]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).

4.2.2. Usage of information on borrowers

We now study how M&A and SIP use information on credit merits. We find two things. First, M&A banks are more likely than SIP banks to rely on hard information when inspecting a new borrower's credit profile. Second, SIP banks exhibit uncoordinated lending policies vis-à-vis the same new borrower in the same period.

In line with Stein (2002), we expect the loan officers in centralized organizations to rely more heavily on hard information when setting lending conditions than those in decentralized ones. To support this intuition, we should find that M&A banks are more likely to use hard information than SIP banks. We then inspect the data on banks' requests for information on the credit history of a new applicant for a loan. Such information satisfies Liberti and Petersen (2019) definition of hard information, because it is verifiable, easy to store and transmit, and its content is independent of its collection. We then compute the number of requests for information submitted by each group (M&A and SIP) from the year-month in which consolidation took place up to November 2011. To normalize this number, we divide it by the total credit granted by that group (in thousands of euros). We obtain that the number of requests for information per thousand euros of credit is equal to 0.14 for SIP and 0.16 for M&A, corresponding to M&A banks having a 15% larger propensity per thousand of euros of credit granted to tap the credit registry to inspect the past performance of an applicant.

Like M&A banks, post consolidation SIP banks were compelled to set up a new, central risk management system. However, the decentralized nature of SIP may imply a different use of the credit-merit analyses produced by the risk management unit, depending on loan officers' incentives. This can, in turn, impair the coordination of lending policies within group. To support this intuition, we again use the data on requests for information on new borrowers. We construct a dummy variable that is equal to one if (i) a savings bank belonging to a given SIP requested information on a borrower and (ii) we do not observe an increase in the credit balance with that borrower. The dependent variable is then 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 and on SIP group-firm fixed effects.[16]

[16]We cannot perform this analysis for M&A banks, because after consolidation they only report information at the group level to the credit registry.

The use of these fixed effects implies that our sample is restricted to those observations for which two savings banks within a given SIP group request information on the same new borrower during the period under consideration. This allows us to effectively capture whether a given firm is treated likewise by the savings banks within the same SIP. If all savings banks within a SIP treat a firm's loan application in the same way, the individual savings bank dummy variables should not be statistically significant. Table V shows that, in three out of four of the SIP for which we can estimate the coefficient of interest,[17] a savings bank treats a loan application submitted by the same firm differently with respect to the average savings bank in the same SIP. Given that each SIP has a different number of savings banks, to guarantee confidentiality, in the table we only report the coefficient for the savings bank dummy with the lowest p-value within each SIP group.

4.2.3. Poaching within the same SIP

We now show that, post consolidation, SIP savings banks kept poaching creditors with a previous lending relationship with savings banks within the same SIP. We say that within-group poaching takes place when a firm with an existing relationship with a savings bank in group j opens a new credit relationship with another savings bank belonging to the same group. We then compute the number of *new* credit relationships with any savings bank that is part of any SIP from the year-month in which a SIP formed up to November 2011. We find that 31% of these new relationships happen to be with a different savings bank within the same SIP.

In the presence of coordinated credit policies, in an effort to limit within group competition, we should observe a reduction in the extent of poaching within the same group compared to the pre-consolidation period. In fact, if anything, we find the opposite. The share of new relationships featuring within-SIP poaching was 29% between November 2007 and the year-month in which consolidation took place.[18]

[17] In the remaining cases, we cannot estimate the coefficient because of the lack of observations on common requests for information within each SIP and period.

[18] This comparison cannot be performed for M&A banks, because after consolidation they only report group-level information to the credit registry.

Table V: Uncoordinated lending conditions across SIP banks

	Rejected Application
Savings Bank in SIP Group 1	0.200*
	[0.117]
Savings Bank in SIP Group 2	0.252*
	[0.131]
Savings Bank in SIP Group 3	0.065
	[0.117]
Savings Bank in SIP Group 4	0.038**
	[0.016]
Savings Bank in SIP Group 5	.
	.
Savings Bank in SIP Group 6	.
	.
Observations	1,005
R-squared	0.884
SIP Group-Firm FE	YES

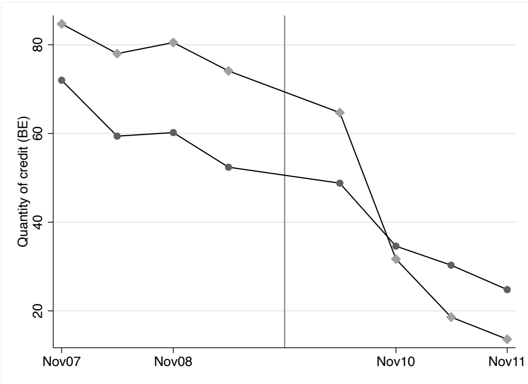
Notes: In this table, we test whether savings banks within a given SIP have similar lending policies after forming the group. We restrict our sample to savings banks in our sample that consolidated through a SIP. The analysis is conducted during the time period between the semester of the formation of SIP-group j 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 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. We regress this variable on dummy variables for each specific savings bank (the omitted term refers to one of the savings bank in each given SIP) and on SIP group-firm fixed effects. For each SIP group (1–6), we only report the coefficient for the savings bank dummy with the lowest p-value. We report 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.

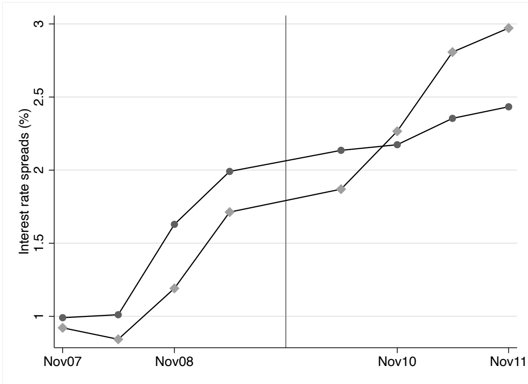
4.3. Unconditional evidence

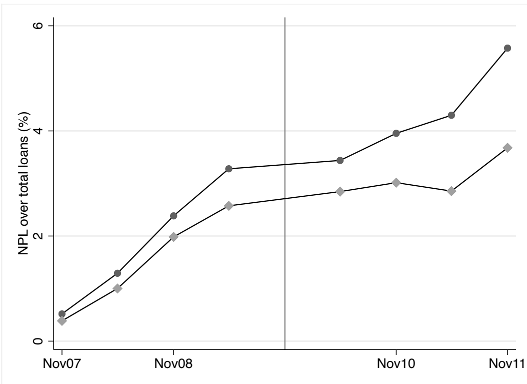
In Figure 3, we consider the time span between four semesters before, and four semesters after the Law to plot the pattern of our three main outcome variables: (i) the average amount of outstanding credit granted to the universe of non-financial corporations (top-left panel); (ii) the average spread 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). We do this separately for the M&A and the SIP banks in our sample.

The plots confirm that these variables satisfy the common trend property. They also provide unconditional evidence that is in line with our predictions on

Figure 3: 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), 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 the month in which the Law was passed (November 2009). Since the information is aggregated at the group-level (M&A or SIP), we do not report the confidence intervals.

the effects of M&A's stronger market power. The evolution of the new credit granted by M&A and SIP banks (top-left panel) 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 Law was passed 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

The comparison between M&A and SIP banks allows us to identify the differential impact of market power on the supply and the performance of credit, controlling for consolidation-related efficiencies. In this section, we present the three specifications we use in our analysis. To document the separate effects of M&A and SIP, we later use the group of Spanish commercial banks.

Consider a bank group j dealing with firm i at time t (corresponding to a semester).[19] The baseline econometric model we use for the analysis of bank credit is:

$$\begin{aligned} y_{jit} &= \alpha_1 \text{M\&A}_j + \alpha_2 \text{Post}_{jt} + \alpha_3 (\text{M\&A}_j \times \text{Post}_{jt}) \\ &\quad + \beta X_{jt-h} + \gamma Z_{it-h} + \zeta \text{FROB}_{jt} + \delta_{kmst} + \epsilon_{jit}. \end{aligned} \tag{2}$$

[19] In all our regressions, we find similar results when considering monthly or annual growth.

We denote by y_{jit} the semiannual growth rate of the (log) volume of total credit between November 2007 and November 2011. Post_{jt} is specific to each bank group j, and is equal to one starting from the end of the semester in which group j (M&A or SIP) formed. $\text{M\&A}_j$ is a dummy that equals one if the bank participated in a M&A, 0 if SIP. The coefficient of interest is α_3. 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-h} and Z_{it-h}). Specifically, X_{jt-h} includes a bank's total assets, capital ratio, volume of credit over deposits and profitability (ROA). Z_{it-h} includes firm leverage, liquidity, profitability (ROA), and total assets. The value of the variables in X_{jt-h} and Z_{it-h} are taken in the end of the year before the beginning of each semester in which we compute the semiannual growth rate. 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.[20]

We will use the model in equation (2) to identify the differential impact of M&A and SIP on savings banks' loan portfolio composition. There we split the sample of firms into risky and safe firms based on the distance from default using a variation of Altman's Z-score.

We now turn to the analysis of the relative effects of consolidation modes on interest rate spreads. Since the information on interest rates is collected at the bank-month level, we aggregate it across maturities and use the following model:

$$w_{jt} = \alpha_1 \text{M\&A}_j + \alpha_2 \text{Post}_{jt} + \alpha_3 (\text{M\&A}_j \times \text{Post}_{jt}) + \beta X_{jt-h} + \zeta \text{FROB}_{jt} + \iota_{jt}, \quad (3)$$

where w_{jt} denotes the spread between the nominal interest rate and the three-month Euribor. In this case, Post_{jt} is equal to zero between November 2007 and the month in which group-j consolidation took place, and one from the month of consolidation and November 2011. The specification includes bank controls (X_{jt-h}), FROB contributions (FROB_{jt}) and no firm control.

[20] 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.

Finally, for the analysis of NPL, we use:

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

The dependent variable is the proportion of NPL over total loans of a given firm i reported by a bank group j at the end of each semester between the date of consolidation and November 2011.

In this analysis, we consider only the firm-savings bank pairs featuring no credit relationship at the consolidation date. Consequently, there is no Post_{jt} dummy. We do this because we cannot identify the specific loan facility that turns out to be non-performing in the post period. If we were to consider the firms with a relationship with a bank before consolidation, it could happen that some NPL reported afterwards is associated to lending originated before consolidation. The main advantage of this approach is that loan refinancing, or ever-greening, cannot impair the interpretation of our findings. Finally, the specification contains firm and bank controls (Z_{it-h} and X_{jt-h}, respectively), and controls for the value of FROB contributions (FROB_{jt}).

All models are estimated using OLS. For the models in equations (2) and (4) we cluster standard errors at the industry-province-size and bank group j-province level. We consider a two-way clustering that includes the interaction between bank group j and province because, to study bank competition, the relevant local market is typically considered to be the province. For the model in equation (3) clustering is at the bank-group j and month level, corresponding to the level of aggregation of the information on interest rates.

4.4.1. Province-level variation

The literature on bank mergers exploits heterogeneity in the geographic location of merging banks to distinguish between in-market and out-of-market mergers (Sapienza, 2002). However, similar to Erel (2011) for the US, separating in-market and out-of-market consolidations in the Spanish savings banks' sector is difficult. There are in fact too few observations for out-of-market consolidations, as most of the savings banks operate in many markets, and most consolidations involve more than two savings banks. We instead exploit heterogeneity in the extent to which savings banks overlap within the same province.

We distinguish between the provinces in which all M&A and SIP banks had a small market share before the Law was passed, and the provinces where they had large market shares. In practice, to confirm the importance of market power after consolidation, we need a measure for how large a consolidating savings bank is compared to the other banks in the same province in a given point in time. We rank the Spanish provinces based on the level of the market share of the largest bank in each province (including commercial and cooperative banks), computed in terms of the volume of lending. We then take the 25th percentile of this distribution. 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 the 25th percentile of the distribution. 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 the 25th percentile of the distribution and that the largest M&A and SIP bank was in the top 5 of all banks in the province.[21]

We will run our empirical models in equations (2) and (4) using data from the provinces where M&A and SIP banks are comparably large or comparably small. For the analysis of credit supply, we take the distribution of market shares in November 2007. For the analysis of NPL, we take the distribution of market shares in November 2009, because we focus on firm-savings bank pairs featuring no credit relationship at the consolidation date. We use these tests to show how the capability to exercise market power interacts with the different organizational structure of M&A and SIP. Lending decisions are taken at the province level, thus we should find that that the market power effect is limited if M&A and SIP banks are comparably small in a given province. Instead, we should find the expected results if M&A and SIP banks are comparably large within the same province.

5. Empirical results

5.1. Quantity and price of credit

To begin with, we study the differential effect of M&A and SIP on the supply of credit in the economy. Table VI reports the estimates of equation (2) using as dependent variable the semiannual growth rate of the (log) volume of total credit between November 2007 and November 2011.

We find that, compared to SIP banks, M&A banks extend less credit. The estimate in column (1) implies that, compared to SIP banks, M&A banks cut

[21] We considered different criteria to distinguish between comparably small and comparably large banks and found similar results.

Table VI: Supply of credit

	(1)	(2)	(3)	(4)
	ΔLog(Credit)			
VARIABLES	All	Excluding Bankia	Comparably Large	Comparably Small
Post	-0.001	-0.007	0.002	-0.014
	[0.016]	[0.018]	[0.023]	[0.026]
M&A	-0.008	-0.019	0.012	-0.021
	[0.011]	[0.016]	[0.014]	[0.016]
Post x M&A	-0.028**	-0.040***	-0.037**	-0.018
	[0.012]	[0.014]	[0.018]	[0.023]
Observations	2,563,725	2,114,122	537,815	710,890
R-squared	0.111	0.122	0.153	0.104
Industry-Location-Size-Time FE	YES	YES	YES	YES
Bank Controls	YES	YES	YES	YES
Firm Controls	YES	YES	YES	YES

Notes: The dependent variable is the semiannual growth rate of the (log) volume of total credit between November 2007 and November 2011. In column (1) we consider the full sample of firms. In column (2) we exclude Bankia from the sample of savings banks. In column (3) 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 (corresponding to 13.6%), and where the largest SIP and M&A bank was in the top 5 banks of that province in November 2007. In column (4), 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 2007. 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 starting from the end of the semester in which group j (M&A or SIP) formed. The set of control variables includes bank characteristics such as Log(TA), Capital Ratio, Credit/Deposits, ROA, (FROB funds)/TA. We also use the following firm characteristics as control variables: Total Liabilities/TA, Liquidity/TA, ROA, Log(TA). Robust standard errors (in brackets) are clustered at industry-province-size and bank group-province 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.1.

lending by about 3% on a semi-annual basis, or about 12,600 euro per firm per semester. The use of industry-location-time-size fixed effects means that this coefficient captures the change in credit at the extensive and at the intensive margin.[22] The non-significant coefficient on M&A confirms that there are no differences in the supply of credit before consolidation.[23] In column (2), we check

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

[23]Despite the use of industry-location-size-time fixed effects, the coefficient on Post can be estimated in columns (1)–(3) because the associated dummy is defined at bank-time level, and

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.

To test for the relevance of potential omitted variables, we follow the methodology proposed by Oster (2019). We run a version of our specification in column (1) without controls and fixed effects. We then compute the bias-adjusted treatment effect to test whether the identified set for the treatment effect includes zero. We show that the estimated bound for the treatment coefficient always excludes zero. We conclude that the differential effect of M&A on credit supply is not driven by omitted variables governing other demand or supply side mechanisms. The details are in Table B-II (Appendix A.2).

In column (3), 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 2007. As expected, our coefficient of interest is negative and statistically significant. In column (4), we run the regression on the sample of firms that operate in the provinces where M&A and SIP banks have comparably *small* market shares in November 2007. Since these banks are relatively small, they should have little capability to exercise market power at the local level independently of their consolidation mode. We find that the coefficient of interest is not statistically different from zero (and smaller in magnitude with respect to those in columns (1)–(3)).

To interpret these results, we build on the evidence in Section 4.2 and the conceptual framework in Section 2.2. Our effects are driven by differences in the organizational structure of M&A and SIP, and the implications for the exercise of market power. They are not driven by the possibility that M&A and SIP banks differ in the baseline, or by differences in the efficiency gains generated by consolidation.

In Table VII, we run equation (3) using bank-month level information on newly issued loans' interest rates. 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 credit 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 the bank-month level. In column (1), we consider the full sample of banks and in column (2) we exclude Bankia. We cannot perform the analysis using data from provinces where M&A and SIP banks are comparably large or small because the information on interest rates is aggregated at the bank-month level in our data.

in the first semester not all savings banks were consolidated.

Table VII: Interest rate spreads

	(1)	(2)
	Weighted Average IR Spread	
VARIABLES	All	Excluding Bankia
Post	0.448*	0.400
	[0.229]	[0.256]
M&A	-0.265	-0.385*
	[0.216]	[0.205]
Post x M&A	0.393*	0.431*
	[0.201]	[0.227]
Observations	588	539
R-squared	0.357	0.346
Bank Controls	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 between 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 the month of group-j consolidation. The set of control variables includes the same bank characteristics as in Table VI. 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 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 column (1) we consider the full sample of banks. In column (2), we exclude Bankia. Robust standard errors (in brackets) are clustered at the bank group and 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.1.

We find that, compared to SIP banks, M&A banks apply higher interest rate spreads.[24] Back-of-the-envelope calculations based on the coefficient in column (1) suggest that a loan granted by a M&A bank is 42 bp more expensive than that granted by a SIP bank post consolidation. Thus, the premium charged for this loan size by M&A banks corresponds to 13% 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 VI, and with the prediction on the stronger market power effect of M&A. As in Table VI, the non-significant coefficient on M&A in column (1), our main specification, shows that there is no statistical difference in the interest rate spreads before consolidation.

We next look at the differential impact of M&A and SIP on the stability of the banking system.

5.2. Consolidation modes and financial stability

We run equation (4) using information on the volume of savings banks' NPL. The results are in Table VIII. The dependent variable is the average proportion of NPL over total loans of a given firm reported by a bank group at the end of each semester between the date of group-j consolidation and November 2011.

We find 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 1 pp less for M&A banks than for SIP banks. As in Tables VI and VII, we obtain the same results when excluding Bankia (column (2)). Since we consider the bank-firm pairs that have no credit relationship at the consolidation date, our results are produced by loans granted after consolidation, and thus cannot be explained by loans' ever-greening or refinancing. To test for the relevance of potential omitted variables, we follow Oster's (2019) methodology. 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-II in Appendix A.2).

In analogy to Table VI, we find our differential effects on NPL only in the provinces where the capability to exercise market power is comparably large, not where it is comparably small. We first report the results of a regression in which we restrict the analysis to the firms that operate in the provinces where savings banks are comparably *large* (column (3)). The estimated coefficient is statistically significant and similar in magnitude to the one in column (1). Finally, we run our

[24]We find similar results when using 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.

Table VIII: NPL accumulation

	(1)	(2)	(3)	(4)
	NPL			
VARIABLES	All	Excluding Bankia	Comparably Large	Comparably Small
M&A	-0.007**	-0.003*	-0.005**	-0.004
	[0.003]	[0.002]	[0.002]	[0.003]
Observations	587,812	439,030	247,587	82,296
R-squared	0.184	0.202	0.184	0.263
Industry-Location-Size-Time FE	YES	YES	YES	YES
Bank Controls	YES	YES	YES	YES
Firm Controls	YES	YES	YES	YES

Notes: This table reports the results obtained from a regression analysis in which the dependent variable is the average proportion of NPL over every semester of the period spanning between the announcement of group j-formation (M&A or SIP) and November 2011. The explanatory variable of interest is the dummy for M&A and SIP. In column (1) we use the whole sample of firms, in column (2) we exclude Bankia from the sample of savings banks. In column (3) 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 (corresponding to 13%), and where the largest SIP and M&A bank was in the top 5 banks of that province in November 2009. In column (4), 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. Robust standard errors (in brackets) are clustered at industry-province-size and bank group-province 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.1.

regression on the sample of firms that operate in the provinces where savings banks are comparably *small* (column (4)). The coefficient of interest is not statistically different from zero.

We next document how the two consolidation modes differentially affected the composition of banks' loan books, the banks distance from default, and the proportion of NPL reported by banks that did not participate in the consolidation program.

5.2.1. 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 using a variation of Altman's Z-score computed for Spanish firms (see Appendix A.1 for the details). We then analyze the differential propensity of M&A and SIP to extend credit to safe and risky firms by running the model in equation (2) separately for safe and risky firms. The dependent variable is the semiannual growth rate of the (log) volume of total credit between November 2007 and November 2011. The results are in Table IX.

Table IX: Banks' loan portfolios

	(1)	(2)
	ΔLog(Credit)	
VARIABLES	Risky	Safe
Post	0.009	-0.013
	[0.017]	[0.019]
M&A	-0.008	-0.010
	[0.011]	[0.012]
Post x M&A	-0.038**	-0.017
	[0.011]	[0.015]
Observations	1,162,048	1,325,607
R-squared	0.151	0.146
Industry-Location-Size-Time FE	YES	YES
Bank Controls	YES	YES
Firm Controls	YES	YES

Notes: This table extends the analysis in Table VI to study the differential proportion of ex-ante safe and risky firms in savings banks' loan portfolios. Firms are classified as safe or risky based on a variation of an Altman's Z-score for Spanish firms (see Appendix A.1 for the details). As in Table VI, the dependent variable is the semiannual growth rate of the (log) volume of total credit between November 2007 and November 2011. We split the sample of firms based on the value of their risk indicator. To obtain the risk indicator, we use information at the end of the year before the beginning of each semester in which we compute the semiannual growth rate. The set of control variables are the same as in Table VI. Robust standard errors (in brackets) are clustered at industry-province-size and bank group-province 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.1.

We find that the relative impact of M&A and SIP banks on the proportion of NPL documented above can be explained by a significant difference between M&A and SIP in the supply of credit to risky borrowers (column (1)). There is no statistically significant difference between M&A and SIP in the propensity to extend credit to safe firms (column (2)). In both columns, the fact that the coefficient on M&A is not statistically significant means that there is no evidence of a differential treatment of risky and safe firms by M&A and SIP banks before consolidation.

5.2.2. Bank groups' default risk

The evidence thus far shows that M&A banks report a higher proportion of NPL post consolidation (Table VIII). Table IX then shows that the differential result on NPL accumulation can be explained by M&A banks' smaller propensity to extend credit to risky firms. We now analyze the differential impact of consolidation modes on banks' default risk. Specifically, following Laeven and Levin (2009), we proxy default risk by computing the inverse of banks' distance from default. The results are in Table X.

We find that M&A banks' default risk is significantly lower than SIP banks'. Moreover, before consolidation, distance from default is comparable across M&A and SIP banks, as witnessed by a non-significant coefficient on the M&A dummy.

5.2.3. Spillover effects

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 registry information on the requests for information submitted by a bank to the credit registry. We check whether a firm rejected by a M&A bank, or by 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 then was non-performing. We do not find any evidence of such spillovers (the results are in Table B-III).

5.3. Separate effects of M&A and SIP

Tables VI and VIII document that, compared to business groups, the exercise of market power by merging banks triggers a trade-off. On the one hand, it reduces credit. On the other hand, it reduces the NPL reported by savings banks. We obtain these results as the differential effect of mergers when compared to

Table X: Banks' distance from default

	(1)
	Bank Default Risk
VARIABLES	All
Post	0.027***
	[0.012]
M&A	-0.004
	[0.003]
Post x M&A	-0.036***
	[0.011]
Observations	509
R-squared	0.116
Bank Controls	YES

Notes: The dependent variable is computed at the bank-time level using the following formula: SD[ROA]/(Equity/Total assets + ROA), where SD[ROA] is the standard deviation of ROA's monthly value in the preceding 12 months. The bank control variables are the same as in Table VI. Robust standard errors (in brackets) are clustered at bank group and 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.1.

business groups. In this section, we use information on commercial banks, which the Law left out of the consolidation program, to measure the separate effects of each integration mode on credit supply and NPL accumulation. The fact that commercial banks were excluded from the consolidation program, and hence did not perform any form of integration, limits the threats to identification. The results of the analysis are in Table XI.

As compared to commercial banks, we find that M&A banks restrict credit supply after the program started. In line with the presumption that the market power effect is stronger for M&A than for SIP, compared to commercial banks, SIP produce weaker differential effects on lending. As for NPL, both M&A and SIP banks report less NPL when compared to commercial banks. Finally, the difference in the proportion of reported NPL across M&A and SIP is statistically significant, and comparable to the one we find in Table VIII.

Table XI: Separate effects of M&A and SIP

	(1)	(2)
	ΔLog(Credit)	NPL
VARIABLES	All	
Post x M&A	-0.033***	
	[0.004]	
M&A	-0.081***	-0.027***
	[0.003]	[0.002]
Post x SIP	-0.012**	
	[0.005]	
SIP	-0.062***	-0.023***
	[0.003]	[0.003]
Observations	4,102,573	895,626
R-squared	0.083	0.213
Industry-Location-Size-Time FE	YES	YES
Bank Controls	YES	YES
Firm Controls	YES	YES

Notes: This table reports the results obtained from a regression analysis in which the dependent variable in column (1) is the semiannual growth rate of the volume of total credit. In column (2), it is the average proportion of NPL over every semester of the period spanning between the announcement of group j-formation (M&A or SIP) and November 2011. In both columns, the post period starts in the second semester after November 2009, because in the first semester some of the savings banks had not consolidated yet. This guarantees that we can compare commercial banks to M&A and SIP banks once all groups had formed. The set of firm and bank controls are the same as in Tables VI and VIII. Robust standard errors (in brackets) are clustered at industry-province-size and bank-province 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 these variables, see Appendix A.1.

6. Welfare analysis

We propose a structural analysis to quantify the welfare implications of the consolidation program. 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 risk) across scenarios.

Although, from an economic point of view, the natural unit of analysis would the province, the credit registry contains information on interest rates at the bank-month level. We will then have to perform the welfare analysis using aggregate information on prices and quantity, in line with much of the structural literature in industrial organization. Using aggregate bank-time level interest rates as opposed to borrower level ones, when the latter data is not available, is common practice among papers estimating structural models of demand for loans (Aguirregabiria, Clark, Wang 2020; Wang, Whited, Wu, Xiao 2020).

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,[25] 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.[26] It reduces the "size of the market" (i.e. the number of potential borrowers that would not 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. We do this to keep the model tractable, and comparable with the reduced form findings, where the reduction in NPL is driven by the drop in quantities due to the market

[25]We do not have data on interest rates at the borrower level, but only at the bank-month level, which prevents us from modeling risk-based pricing. We compensate this lack of data allowing banks to ration based on expected borrowers' default risk.

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

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:

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

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 AC_{bt} are expected average 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) average costs, and express them as a function of quantities:

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

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 average cost curve, Z_{bt} is bank-time varying log of total assets, τ_b are bank fixed effects, and ω_{bt} are IID cost shocks. As we will see, we obtain that average 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 $\mathcal{Q}_{0mt} = \mathcal{M}_{mt} - \sum_{b \in B_{mt}} \mathcal{Q}_{bmt}$.[27] 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 for outstanding loans, and thus loan rates on newly granted loans. This is captured in equation (9) by the effect of total assets on costs. 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.[28]

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

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

[28] 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.

for each M&A group).

Table XII 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.[29]

Table XII: 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
Average Cost (AC_{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 Risk is as in Table X. 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.1).

Estimation results are reported in Table XIII. 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 average cost AC_{bt} of over 43% of its standard deviation. The results are in Table B-IV (Appendix A.2). This means that, consistent with the assumption we make in Section 2.2, banks' average-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

[29]Following Laeven and Levin (2009), we compute D_{bt} by using the same formula as in Table X. 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.

Table XIII: 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.1).

consolidation program. Specifically, we simulate the effects of M&A and SIP, as 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:

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

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.[30]

6.3.1. 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. In the short run, we assume that neither a M&A nor a SIP produces efficiencies in the form of lower average 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):

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

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.

6.3.2. 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

[30] Alternatively, banks' default risk could directly affect borrowers' indirect utilities. We rule out this mechanism because it is more reasonable for depositors (Egan, Hortaçsu, Matvos, 2017) or customers worried about manufacturers' warranty viability (Hortaçsu, Matvos, Shin, Syverson, and Venkataraman, 2011) rather than borrowers to have a disutility from banks' default risk. Consistent with this intuition, we considered a model in which banks' default affects borrowers utility and found that the relative coefficient is not statistically significant.

the reduction in consolidating banks component of average 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 compute 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 XIV reports the average percentage changes in interest rates, quantities, average 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 in all markets. Panel B, instead, reports the average changes in average 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.

6.4.1. Short-run results

The counterfactual with no efficiencies generates on average an increase in interest rates, a decrease in quantities, a small reduction in average 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.

6.4.2. 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 average costs by 0.06%, corresponding to 5.4% of the standard deviation of average costs. In the second row of Panel B we compute by how much banks' default risk 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 XIV: Counterfactual outcomes

Panel A: Short Run		
	M&A Banks	All
% Change Interest Rate	2.83	
% Change Loan Volume	-4.80	
% Change Average 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 Average 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. On the other hand, market power causes a reduction in the volume of non-performing loans, the loans extended to risky firms and the risk of bank default. These results are not driven by differences in the efficiencies generated by mergers and business groups, or by differences between M&A and SIP banks' characteristics before consolidation. Instead, thanks to our wealth of data, we can relate the capability to exercise market power to the differences across consolidation modes in the use of information and coordination of credit policies. 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. As it happened in Spain, bank consolidation programs are typically decided by governments and regulators in times of crisis, as a response to the problems of ailing banks. We already mentioned some examples of restructuring measures featuring bank consolidation in the introduction. The claim of policy makers was that consolidation can reduce the inclination of "overbanked" systems leading to produce excessive NPL stockpiling in times of crisis.[31] The debate during the COVID-19 pandemic makes no difference.[32]

Our contribution to this debate consists in showing 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.

References

[1] Adams, W., Einav, L., and Levin J., 2009. Liquidity Constraints and Imperfect Information in Subprime Lending. American Economic Review 99, 49–84.

[2] Adrian, T., and Brunnermeier, M. K., 2016. CoVaR. American Economic Review 106, 1705–1741.

[3] Agarwal, S., Chomsisengphet, S., Mahoney, N., and Stroebel, J., 2018. Do Banks Pass Through Credit Expansions to Consumers Who Want to Borrow?. Quarterly Journal of Economics 133, 129–190.

[4] Aguirregabiria, V., Clark, R., and Wang, H., 2020. The Geographic Flow of Bank Funding and Access to Credit: Branch Networks, Local Synergies and Competition. Working Paper, University of Toronto.

[5] Allen, J., Clark, R., Houde, J.-F., 2014. The Effect of Mergers in Search Markets: Evidence from the Canadian Mortgage Industry. American Economic Review 104, 3365–3396.

[6] Allen, J., Clark, R., Hickman, B., and Richert, E., 2019. Resolving Failed Banks: Uncertainty, Multiple Bidding & Auction Design. Bank of Canada Staff Working Papers.

[7] Altonji, J., Elder, T., and Taber, C., 2005. Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools. Journal of Political Economy 113, 151–184.

[31] See, for example, "Bank Competition and Bank Supervision" by Ignazio Angeloni (Member of the ECB Supervisory Board at the time), 4 July 2016, available at `https://www.bankingsupervision.europa.eu/press/speeches/date/2016/html/se160704.en.html`.

[32] See "Consolidation in the European banking sector: challenges and opportunities" by Edouard Fernandez-Bollo (Member of the ECB Supervisory Board), 11 June 2021, available at `https://www.bankingsupervision.europa.eu/press/speeches/date/2021/html/ssm.sp210611~87256e1f4b.en.html`.

[8] Banco de España, 2015. Nota Informativa Sobre Ayudas Públicas en el Proceso de Reestructuración del Sistema Bancario Español (2009-2015).

[9] Banco de España, 2016. Financing and Investment Decisions of Spanish Non-Financial Corporations. Chapter 2. Annual Report 2016.

[10] Banco de España, 2017. Informe Sobre la Crisis Financiera y Bancaria en España, 2008-2014.

[11] Berger, A. N., Saunders, A., Scalise, J., and Udell, G., 1998. The Effects of Bank Mergers and Acquisitions on Small Business Lending. Journal of Financial Economics 50, 187–229.

[12] Berry, S., 1994. Estimating discrete-choice models of product differentiation. Rand Journal of Economics 25, 242–262.

[13] Berry, S., and Pakes, A., 1993. Some Applications and Limitations of Recent Advances in Empirical Industrial Organization: Merger Analysis. American Economic Review 83, 247–252.

[14] Bonaccorsi di Patti, E., and Gobbi, G., 2007. Winners or Losers? The Effects of Banking Consolidation on Corporate Borrowers. Journal of Finance 62, 669–695.

[15] Braguinsky, S., Ohyama, A., Okazaki, T., and Syverson, C., 2015. Acquisitions, Productivity, and Profitability: Evidence from the Japanese Cotton Spinning Industry. American Economic Review 105, 2086–2119.

[16] Clarck, R., Houde, J.-F., and Kastl, J., 2021. The Industrial Organization of Financial Markets.

[17] Climent-Serrano, S., 2013. La Reestructuración del Sistema Bancario Español tras la Crisis y la Solvencia de las Entidades Financieras. Consecuencias para las Cajas de Ahorros. Spanish Accounting Review 16, 136–146.

[18] Crawford, G. S., Pavanini, N., and Schivardi, F., 2018. Asymmetric Information and Imperfect Competition in Lending Markets. American Economic Review 108, 1659–1701.

[19] Cuñat, V., and Garicano, L., 2010. Did Good *Cajas* Extend Bad Loans? Governance, Human Capital and Loan Portfolios. In *The Crisis of the Spanish Economy: Economic Analysis of the Great Recession*, S. Bentolila, M. Boldrin, J. Diaz-Gimenez and J. J. Dolado (eds.). Fedea.

[20] Degryse, H, De Jonghe, O., Jakovljevic, S., Mulier, K., and Schepens, G., 2019. Identifying Credit Supply Shocks with Bank-Firm Data: Methods and Applications. Journal of Financial Intermediation 40.

[21] Degryse, H, Masschelein, N., and Mitchell, J., 2011. Staying, Dropping or Switching: The Impact of Bank Mergers on SMEs. Review of Financial Studies 24, 1102–1140.

[22] Egan, M., Hortaçsu, A., and Matvos, G., 2017. Deposit Competition and Financial Fragility: Evidence from the U.S. Banking Sector. American Economic Review 107, 169–216.

[23] Einav, L., and Finkelstein, A., 2011. Selection in Insurance Markets: Theory and Empirics in Pictures. Journal of Economic Perspectives 25, 115–138.

[24] Einav, L., Jenkins, M., and Levin J., 2012. Contract Pricing in Consumer Credit Markets. Econometrica 80, 1387–1432.

[25] Eliason, P. J., Heebsh, B., McDevitt, R. C., and Roberts J. W., 2020. How Acquisitions Affect Firm Behavior and Performance: Evidence from the Dialysis Industry. Quarterly Journal of Economics 135, 221–267.

[26] Erel, I., 2011. The Effect of Bank Mergers on Loan Prices: Evidence from the United States. Review of Financial Studies 24, 1068–1101.

[27] European Banking Authority, 2016. EBA report on SMEs and SME Supporting Factor.

[28] European Commission, 2017. Coping with the International Financial Crisis at the National Level in a European Context.

[29] Farrell, J., and Shapiro, C., 1990. Horizontal Mergers: An Equilibrium Analysis. American Economic Review 80, 107–126.

[30] Favara, G., and Giannetti, M., 2017. Forced Asset Sales and the Concentration of Outstanding Debt: Evidence from the Mortgage Market. Journal of Finance 72, 1081–1118.

[31] Focarelli, D., and Panetta, F., 2003. Are Mergers Beneficial to Consumers? Evidence from the Market for Bank Deposits. American Economic Review 93, 1152–1172.

[32] Fuentelsaz, L., and Gomez, J., 2001. Strategic and Queue Effects on Entry in Spanish Banking. Journal of Economics & Management Strategy10, 529–563.

[33] Giannetti, M., and Saidi, F., 2019. Shock Propagation and Banking Structure. Review of Financial Studies 32, 2499–2540.

[34] Gowrisankaran, G., Nevo, A., and Town, R., 2015. Mergers When Prices Are Negotiated: Evidence from the Hospital Industry. American Economic Review 105, 172–203.

[35] Granja, J., Matvos, G., and Seru, A., 2017. Selling Failed Banks. Journal of Finance 72, 1723–1784.

[36] Gugler, K., and Siebert, R., 2007. Market Power Versus Efficiency Effects of Mergers and Research Joint Ventures: Evidence from the Semiconductor Industry. Review of Economics and Statistics 89, 645–659.

[37] Guiso, L., Sapienza, P., and Zingales, L., 2004. Does Local Financial Development Matter?. Quarterly Journal of Economics 119, 929–969.

[38] Hausman, J., Leonard, G., and Zona, J. D., 1994. Competitive Analysis with Differentiated Products. Annales d'Economie et de Statistique 34, 159–80.

[39] Herrero-Batalla, T., and Teijeiro Pita da Veiga, L., 2013. La Reestructuración de las Cajas de Ahorros tras la Crisis. Cuadernos de Información Económica 229, 113–121.

[40] Hoshi, T., and Kashyap, A. K., 2004. Solutions to Japan's Banking Problems: What Might Work and What Definitely Will Fail. Stigler Center Working Paper.

[41] Houston, J. F., James, C. M., and Ryngaert, M. D., 2001. Where do Merger Gains Come From? Bank Mergers from the Perspective of Insiders and Outsiders. Journal of Financial Economics 60, 285–331.

[42] Hortaçsu, A., Matvos, G., Shin, C., Syverson, C., and Venkataram, S., 2011. Is an Automaker's Road to Bankruptcy Paved with Customers' Beliefs?. American Economic Review 101, 93–97.

[43] International Monetary Fund, 2011. Germany: Financial Sector Stability Assessment. IMF Country Report, No.11/169.

[44] International Monetary Fund, 2012. Spain: The Reform of Spanish Savings Banks. IMF Country Report, No.12/141.

[45] Jiménez, G., Ongena, S., Peydró, J.-L., and Saurina, J., 2014. Hazardous Times for Monetary Policy: What do 23 Million Loans Say about the Impact of Monetary Policy on Credit Risk-taking? Econometrica 82, 463–505.

[46] Laeven, L., and Levine, R., 2009. Bank Governance, Regulation and Risk Taking. Journal of Financial Economics 93, 259–275.

[47] Lester, B., Shourideh, A., Venkateswaran, V., and Zetlin-Jones, A., 2019. Screening and Adverse Selection in Frictional Markets. Journal of Political Economy 127, 338–377.

[48] Liberti, J. M., and Petersen, M. A., 2019. Hard and Soft Information. Review of Corporate Finance Studies 8, 1–41.

[49] Mahoney, N., and Weyl, E. G., 2017. Imperfect Competition in Selection Markets. Review of Economics and Statistics 99, 637–651.

[50] Mayordomo, S., Rodriguez-Moreno, M., and Peña, J. I., 2014. Derivatives Holdings and Systemic Risk in the U.S. Banking Sector. Journal of Banking and Finance 45, 84–104.

[51] Méndez Álvarez-Cedrón, J. M., 2011. *Cajas de Ahorros: Nueva Normativa*, Fundacíon Cajas Ahorros Confederada: Madrid.

[52] Motta, M., 2004. *Competition Policy: Theory and Practice*. Cambridge University Press.

[53] Nevo, A., 2000. Mergers with Differentiated Products: The Case of the Ready-to-Eat Cereal Industry. Rand Journal of Economics 31, 395–421.

[54] Oster, E., 2019. Unobservable Selection and Coefficient Stability: Theory and Evidence. Journal of Business and Economic Statistics 37, 187–204.

[55] Panetta, F., Schivardi F., and Shum, M., 2009. Do Mergers Improve Information? Evidence from the Loan Market. Journal of Money, Credit and Banking 41, 673–709.

[56] Peek, J., and Rosengren, E. S., 1998. Bank Consolidation and Small Business Lending: It's Not Just Bank Size that Matters. Journal of Banking and Finance 22, 799–819.

[57] Petersen, M. A., and Rajan, R. G., 1995. The Effect of Credit Market Competition on Lending Relationships. Quarterly Journal of Economics 110, 407–443.

[58] Sapienza, P., 2002. The Effects of Banking Mergers on Loan Contracts. Journal of Finance 57, 329–367.

[59] Scharfstein, D. S., and Sunderam, A., 2016. Market Power in Mortgage Lending and the Transmission of Monetary Policy. Harvard University Working Paper.

[60] Sovinsky Goeree, M., 2008. Limited Information and Advertising in the U.S. Personal Computer Industry. Econometrica 76, 1017–1074.

[61] Starc, A., 2014. Insurer Pricing and Consumer Welfare: Evidence from Medigap. Rand Journal of Economics 45, 198–220.

[62] Stein, J., 2002. Information Production and Capital Allocation: Decentralized versus Hierarchical Firms. Journal of Finance 57, 1891–1921.

[63] Stiglitz, J. E., and Weiss, A., 1981. Credit Rationing in Markets with Imperfect Information. American Economic Review 71: 393–410.

[64] Vives, X., 2016. *Competition and Stability in Banking: The Role of Regulation and Competition Policy*. Princeton University Press.

[65] Wang, Y., Whited, T. M., Wu, Y., and Xiao, K., 2020. Bank Market Power and Monetary Policy Transmission: Evidence from a Structural Estimation. Journal of Finance forthcoming.

[66] Werden, G. J., and Froeb, L. M., 1994. The Effects of Mergers in Differentiated Products Industries: Logit Demand and Merger Policy. Journal of Law, Economics, and Organization 10, 407–26.

A. Internet Appendix

A.1. Data appendix

The information on loans is obtained from the Banco de España Central Credit Registry (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 850,000 firms in all years between 2006 and 2010 (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.[33] 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 IX. The version of Altman's Z-score we use was developed by Amat, Manini, and Renart (2017) for Spanish firms.[34] It is obtained from the following specification:

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

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.1.1. 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.
- Bank Default risk: SD[ROA]/(Equity/Total assets + ROA), where SD[ROA] is the standard deviation of ROA's monthly value in the preceding 12 months. We then winsorize its value between 0 and 1.

[33] 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

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

- (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.
- 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.
- NPL: the ratio of NPL over total loans.
- Post: dummy variable that is equal to one after the date of consolidation of each group j and November 2011. 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

- ΔLog(Credit): semiannual change in the log value of credit balance between November 2007 and November 2011.
- 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.

A.2. Additional tables and figures

Table B-I: List of consolidations (M&A and SIP)

(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: Omitted variable test

Panel A		
	(1)	(2)
VARIABLES	ΔLog(Credit)	
Post	-0,002	0.001
	[0.011]	[0.016]
M&A	-0,004	-0.008
	[0.002]	[0.011]
Post x M&A	-0.016***	-0.028**
	[0.003]	[0.012]
Observations	2,563,725	2,563,725
R-squared	0.003	0.111
Industry-Location-Size-Time FE	NO	YES
Bank Controls	NO	YES
Firm Controls	NO	YES
Identified Set	[-0.032,-0.028]	
Panel B		
	(1)	(2)
VARIABLES	NPL	
M&A	-0.003***	-0.007***
	[0.001]	[0.003]
Observations	587,812	587,812
R-squared	0.001	0.184
Industry-Location-Size FE	NO	YES
Bank Controls	NO	YES
Firm Controls	NO	YES
Identified Set	[-0.008,-0.007]	

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 semiannual growth rate of the log value of credit (Panel A) and proportion of NPL (Panel B) (for additional details, see Tables VI and VIII). 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-III: NPL spillover

	(1)	(2)
VARIABLES	NPL of Banks Outside the Restructuring Program	
Loan Application Rejected by M&A Bank	-0.003	
	[0.017]	
Loan Application Rejected by M&A or SIP Bank		-0.008
		[0.012]
Observations	25,815	72,918
R-squared	0.230	0.208
Industry-Location-Size-Time FE	YES	YES
Average Bank Controls	YES	YES
Firm Controls	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 (column (1)) and a M&A or a SIP (columns (2)). The analysis is conducted at the firm level. Hence, the dependent variable 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 column (1) 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 between the consolidation date of each group j and November 2011. In column (2), 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 between the consolidation date of each group j and November 2011. The set of firm-level control variables we use are the same as in Table VI, 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., (2)) 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). Robust standard errors (in brackets) are clustered at the industry-province-size 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.1.

Table B-IV: Average 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.

A.3. 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.[35] 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:[36]

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

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

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.[37] 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 index minus 10-year sovereign bond.

We replace the coefficients obtained from equations (C-1) and (C-2) using

[35] 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.

[36] 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.

[37] 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.

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):

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

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:

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

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.