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Do bank branches matter? Evidence from mandatory branch closings

Autores:

Gabriel Jiménez
Banco de España

Alfredo Martín-Oliver
Universitat de les Illes Balears

José-Luís Peydró
Imperial College London y Universitat Pompeu Fabra

Anna Toldrà-Simats
Universidad Carlos III de Madrid

Sergio Vicente
Université du Luxembourg

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Pseudonym: The MoU Team

ABSTRACT

We study the real effects of bank branch closures on Small and Medium Enterprises (SMEs).

For identification, we exploit a European Commission mandate to shut down a number of bank branches in Spain in 2012. We find that the previous clients of a closed bank branch experience a credit cut of about 25% on average. This reduction in credit significantly reduces SMEs' likelihood of survival. Moreover, it has sizeable negative effects on the investment, employment, sales, and productivity of surviving firms. These results are driven by the inability of SMEs to replace a credit relationship following the closing of a bank branch. We also observe negative effects at the municipality level. Our results raise concerns about the real effects of the drastic downsizings of bank branch networks around the world and the unintended consequences of such measures on countries' governments' efforts towards levelling up.

1. INTRODUCTION

Banks constitute the primary source of external finance for Small and Medium Enterprises (SMEs).

Commentators and researchers have identified various reasons that explain the traditional reliance of SMEs on banks to fund their operations. First, SMEs are private companies and, as such, they possess less publicly available information than large public firms, making it difficult for financial analysts and investors to assess their ex-ante creditworthiness. Second, also due to the lack of public disclosure, the activities of SMEs are hard to verify which enhances the value of proximity banking and the repeated interactions between banks and their clients that occur over long-term firm-bank relationships. The role of loan officers in proximity banking is to collect and analyze information about the prospective clients to reduce ex-post risk-taking by banks. Most of the times, due to the lack of hard information, loan officers rely on more subjective (soft) information to grant loans.[1] By mitigating adverse selection problems, loan officers reduce ex-post delinquencies, facilitating access to better ex-ante credit conditions.

Oftentimes, when a bank branch closes down, the relationship between the loan officer of the closed branch and the firm is lost. Typically, when a branch closes down, the bank automatically transfers the firm's loan-and-account profile to another of its branches. Sometimes, this alternative branch is not too far from the previous one and it employs part of the personnel from the closed branch. However, it is also the case that banks assign these customers to larger and considerably more distant branches where they deal with SMEs in a more standardized and impersonal way by making more use of automatized credit scoring systems based on hard information. Consequently, when a firm-branch relationship is lost due to branch closings, the soft information gathered in previous interactions between the loan officer and the firm is lost or no longer used.

In this paper, we study the causal effects of bank branch closings on SMEs' investment, employment, revenues, productivity, and their probability of survival after

[1] Liberti and Petersen (2017) define hard information as quantitative, easy to store and transmit in impersonal ways, and its information content is independent of the collection process. In contrast, soft information, as they define it, is of qualitative nature, difficult to replicate, transmit or store, and its content depends on the person collecting that information.

losing their bank branch. We then study the effect branch closings on firms' ability to borrow and assess whether the negative real effects on firms, if any, occur through the credit channel. We also uncover the presence of heterogeneous effects across firms. Specifically, we are interested in studying whether firms with more hard and soft information suffer less from the negative consequences of losing their bank branch. Moreover, we take advantage of the contraction of the Spanish bank branch network and the transition towards more automatized credit scoring systems to study the efficiency of credit allocation by banks after the Spanish reform and its effects at the local level. As we explain below, whereas the objective of the banking reform in Spain was to restore the stability of the financial system, such a drastic reduction in the number of bank branches may have had unintended consequences that increased the disparities across municipalities.

Since the onset of the 2007-2008 financial crisis, the banking sector has witnessed an unprecedented number of branch closures all over the world. For instance, in the European Union, more than 74,000 branches have closed their doors between 2008 and 2019, reducing the number of branches by one-third in a decade. Far from slowing down, this trend has even accelerated in the recent years. For example, in Spain, in November 2020, Santander Bank announced the closing of around one-third of its branch network, amounting to 1000 branches. This was not an isolated event. The number of branches in the US declined by 3000 in 2021, adding to 13,000 branch closures between 2008 and 2020; and half of the UK branch network has either shut down or been scheduled for closure between 2015 and 2021, with a total of 736 shutdowns in 2021 almost doubling the figures from 2019 and 2020.

One of the main consequences of bank branch closings is the substitution of loan officers' routine activities by automatized credit scoring systems and standardized performance evaluation procedures, both used to determine the creditworthiness of companies. Due to these changes, the substantial downsizing of the banking system branch network has raised concerns about the effect on the availability of credit to SMEs. Indeed, if the automatized screening and monitoring systems cannot fully replace loan officers' activities despite their cost-saving advantage, one may expect that (at least some) firms experience a reduction in their ability to borrow and, consequently, a disruption in their economic activity following the closure of a bank branch.

Empirically, we test these ideas by estimating a difference-in-difference model where the explanatory variable corresponds to bank branch closures. The main empirical challenge that we face is that the closure of bank branches is typically not exogenous. Indeed, one of the main reasons for closing a bank or several of its branches is the poor performance of that bank or branch. If the poor performance is due to the low creditworthiness of the SMEs to which the bank lends, the interpretation of a causal effect in our difference-in-difference estimations would be compromised. For identification, we rely on the "Memorandum of Understanding on Financial Sector Policy Conditionality Agreement between the Kingdom of Spain and the Heads of State and Government of the Euro Area" (henceforth MoU) signed on the 20th of December, 2012.[2] The MoU came as a result of the profound crisis of the Spanish banking sector and it established a strict conditionality agreement by which the European Financial Stabiltiy Facility (EFSF) would provide funds to Spain to recapitalize the troubled Spanish banks with the purpose of restoring financial stability.

The banking crisis in Spain had started as a consequence of the economic crisis of 2008, which revealed the fragility of the Spanish growth model (based on the real estate bubble), the lack of competitivity of the Spanish economy, and its large fiscal deficit. During the 14-year period of uninterrupted economic growth that preceded the crisis, the Spanish banking sector had been expanding and disproportionately increasing the weight of the credit allocated to the real estate and construction sectors. These sectors had exploded due to low interest rates and continuously increasing valuations of buildings and property. Once the crisis hit, it became very difficult, if not impossible, for the troubled Spanish banks (i.e. most of them, except the largest and most diversified) to access financial markets to attract the necessary capital to lend to the productive sector. One of the resolutions of the MoU was that the distressed banks would have to close a large percentage of their branches in a very specific manner. Precisely, as part of the conditionality agreement, the MoU mandated that, once the troubled banks were identified, each recapitalized bank would have to close all of its bank branches that fell outside the core region of the bank as part of its reorganization plan. The core region is defined as the region where the bank is headquartered and where it established its very first branches. The MoU identified 8 troubled banks that would need recapitalization from the European funds. These banks and their core regions are detailed in Figure 1. For example, Catalunya Caixa had four core regions, which

[2] The Memorandum of Understanding can be found here: https://ec.europa.eu/economyfinance/euborrower/mou/2012–07–20–spain–mouen.pdf

are the four provinces of Catalonia (Barcelona, Tarragona, Lleida and Girona), and the non-core regions correspond to the rest of the regions in Spain.

This large scale downsizing that obliged closing all the banks' branches outside the core regions indiscriminately is the source of exogenous variation that we use for identifying our causal effect. Specifically, our identification strategy relies on comparing the future fate of SMEs that lost their bank branch due to a non-core region closing mandated by the MoU, to other SMEs that did not lose their bank branch. The key underlying assumption of this identification strategy is that of parallel trends: the SMEs affected by non-core region branch closings would not have evolved differently in terms of their investment, activity, and survival, relative to the non-affected SMEs, had the closings of non-core region bank branches not taken place. Precisely because of the indiscriminate nature of the branch closings in the non-core regions, i.e. all of them had to close, there is a priori no reason why the SMEs that obtained credit from these branches should be worse than the SMEs that obtained credit from non-closing branches. Specifically, it is important to notice that, in the estimations, the SMEs included in the control group have a credit relationship with a non-troubled bank. To the extent that the troubled banks had financial difficulties for reasons other than the financial health of those SMEs, then the parallel trends assumption of the difference-in-difference estimation is not violated. Below we provide reasons why we think that is the case and several tests that provide support for our assumption.

Our results indicate that the closure of a bank branch increases SMEs probability of going out of business by about 36% when the company had an exclusive credit relationship with the closed branch. Moreover, we show that surviving firms' assets, employment, sales, and productivity decline by 9.2%, 7.5%, 13.6%, and 6.5%, respectively. The channel through which a branch closure affects firms is the impairment of the firm-branch relationship and subsequent inability of the SME's access to credit. In particular, we find that firms previously borrowing from a closing branch experience a 7.6% contraction in their credit. Moreover, this credit decline elevates to 11.5% in the case of firms with a single credit relationship.

To further assess whether the mechanism through which firms reduce their activity is via the inability to access credit, we also estimate an instrumental variable model in which we instrument SMEs' credit with MoU-mandated branch closures. We find that the credit reduction due to mandatory branch closings leads to a 6.3% increase in the probability of going out of business. Among surviving firms, we find that a 1% reduction in credit due to mandatory branch closings leads to a decline in firms' assets of about 0.12%, a decline in SMEs' number of employees of about 0.40%, a reduction in sales of about 0.73%, and a reduction in TFP of 0.17%.

We further inspect the effect of losing a bank relationship by distinguishing between firms with one and multiple credit relationships before the MoU-induced closings. We find that firms with multiple relationships rely on their alternative banking partners and mitigate the impact of a branch closure. This finding supports the theory that a branch closure reduces credit availability through the inability of firms to replace the broken relationship. We also exploit the granularity of our data and estimate a model `a la Khwaja and Mian (2008) with loan-level data including either firm fixed effects or firm-year fixed effects for firms with multiple bank relationships. Under the assumption that firms' credit demand does not vary across banks, including time-varying firm fixed effects allows us to identify the effect of credit supply shocks. Consistently with our hypothesis, we find that credit cuts mainly arise from closing branches.

We use the same negative shock brought by the MoU to study SMEs' heterogeneity in obtaining credit. We find that SMEs with more hard and soft information are more likely replace the lost branch with another one, either from the same or even a new bank. As a consequence, these firms are more likely to survive and they are able to invest more and to generate more revenues relative to firms that are not able to keep or replace their bank branch. We also take advantage of the destruction of soft information brought by the conditionality agreement to study whether banks allocate credit more or less efficiently after the MoU. If we agree that, from an economic point of view, it is efficient to allocate credit to its most productive uses, that is, by giving loans to the most productive firms, we should find that in the data. We do not. Interestingly, we find that banks do not distinguish between more or less productive firms. Instead, it seems that banks tend to allocate credit based on their ability to repay.

Finally, we study implications of branch closings at the municipality level. Motivated by the increasing government efforts towards levelling up, we are interested in understanding whether the drastic reductions in the Spanish bank branch network had (unintended) consequences that increased inequalities across regions in Spain. We obtain initial evidence that suggests that this is the case.

Regarding our identification strategy, the firms included in our treated group are those that we consider exogenously treated due to the mandated branch closures. Our control group includes firms that were not affected by a closing, either because their branches did not belong to a troubled bank (like for example Banco Santander, Banco BBVA or Caixabank) or because they belonged to a troubled bank that did not close that branch because it was located in the bank's core region. When comparing treated firms with firms borrowing from healthy banks, one may argue that the creditworthiness of firms borrowing from branches affected by the MoU was lower than that of firms in the control group. After all, the MoU applied to bank corporations facing solvency issues. Also, when comparing treated firms with firms borrowing from troubled banks in their core region, one could argue that the branches outside their core regions allocated loans that were of lower quality than the branches located in the core regions. Insofar as the distance to the headquarters may be negatively correlated with the quality of loans (e.g., Giroud, 2013), this issue may also raise a concern about the comparability of the firms in the control and treatment groups.

We address these points in several ways. First, we test for parallel trends and find that the relevant variables (survival, investment, employment, sales, and productivity) for the firms in the treatment group evolve similarly to those in the control group pre-treatment. This test, however, does not rule out the possibility that treated and control firms may have evolved differently posttreatment had the MoU not taken place. For this reason, we run a battery of additional tests to add confidence to our identification assumptions. For instance, the portfolio of SME loans in institutions affected by the MoU may have included firms in specific industries featuring a worse performance after 2012. Specifically, in Spain, the financial crisis was clearly driven by the real estate and construction sectors bubble. We address this concern by adding industry interacted with year fixed effects to our baseline regression to absorb time-varying changes across sectors and exploit the variation arising from within sectors in each year. We run additional tests removing firms in the real estate or construction industries from the baseline specification to ascertain whether firms in these industries may be the drivers of the results we report. Consistent with this observation, the coefficient magnitudes decrease compared to the baseline specification. However, the coefficients remain significant, suggesting that the effects are not exclusively driven by firms in these industries. Also, it may well be that the local conditions applying to treated firms may have changed differently than in the territories where the control firms were located. We deal with this issue by also adding postal code interacted with year fixed effects to capture the time-varying differences across territories and compare firms within the same postal area in the same year. Finally, we specifically test whether the MoU-mandated closing of a bank branch could be predicted by the performance and financial health of the SMEs to which it was lending. We find that SMEs' characteristics are not able to predict the closing of a bank branch due to the MoU.

All the previously mentioned tests help eliminate the concern that the closed branches targeted by the MoU were granting loans to worse SMEs. Indeed, these results are consistent with the common knowledge that most of the troublesome portfolios of affected banks did not arise from low quality credit to SMEs. Instead, these portfolios were mainly the result of issuing bad mortgages to private individuals or financing large projects in the construction and real estate sectors oftentimes promoted by local governments during the economic boom, like the several well known phantom airports that still make the news in Spain today.[3] Finally, in robustness estimations, we also include, in the control group, firms that have a credit relationship with a troubled bank, but whose branch did not close because it is located in the core region of that bank. Our results remain quantitatively and qualitatively very similar to those reported in the baseline regressions providing further support for our parallel trends assumption.

The paper is organized as follows. Section 2 discusses the theory and related literature. Section 3 describes the data and the variables used in our estimations. We explain the empirical strategy in section 4. We present our results in Section 5. We explore the role of hard and soft information in Section 6. We study micro- and macro-level implications in Section 7. Section 8 concludes.

2. RELATED LITERATURE

This paper relates to a longstanding literature that has highlighted the role of soft information acquisition by loan officers in borrowers' screening (e.g., Petersen and

[3] There exist, unfortunately, several examples of such phantom airports in Spain. One famous example is the airport in Corvera (Murcia) which was financed by several banks, among them, Caja Segovia which later on became part of BFA/Bankia, and Caixa Tarragona which later on became part of Catalunya Caixa, both of them identified by the MoU as troubled banks. Another famous example is the Ciudad Real airport that was largely financed by Caja Castilla la Mancha, the regional bank, which was later on absorbed by Liberbank, and this bank was later on identified by the MoU as troubled bank.

Rajan (1994); Boot and Thakor (2000); Berger, Miller, Petersen, Rajan, and Stein (2005)).[4]

There are several reasons why branch closures may reduce the acquisition of soft information, such as an increase in the distance between borrowers and lenders. Several papers have documented the impact of the distance between borrowers and lenders on lending outcomes. For instance, Petersen and Rajan (2002) argue that local lenders advantageous position to gather soft information leads them to enjoy an informational advantage over distant lenders, while Agarwal and Hauswald (2010) show that proximity facilitates the collection of soft information about borrowers. This finding is consistent with Mian (2006), who suggests that greater distance makes it more costly to produce and communicate soft information, discouraging the acquisition of soft information in the first place. Distance also affects lending outcomes through competition, as in Hauswald and Marquez (2006), who argue that lenders use their local information advantage to soften price competition by creating adverse-selection threats for their rivals or, as in Degryse and Ongena (2005), who show that distance affects loan transactions through spatial price discrimination. Also, the closure of branches typically relocates decision-making centers from small branches to larger and more hierarchical offices. As argued by Stein (2002), and documented by Berger and Udell (2002), Liberti and Mian (2008), Kysucky and Norden (2016), or Skrastins and Vig (2018), the acquisition of soft information may be more difficult in larger and more hierarchical banks.

There are two papers that specifically address the effects of bank branch closures. The closest paper to ours is Nguyen (2019), who finds that branch closures cause prolonged declines in smallbusiness lending and employment around the area of the branch closure.[5] Our paper also shows that branch closures have real effects. Our data, which includes loan information at the firm-branch level, allows us to specifically show that firms who borrow from closing branches experience a decline in their investment, employment, productivity, and sales. Bonfim, Nogueira, and Ongena (2017) show that firms who forcefully switch to a different bank following the closure of their bank branch receive worse loan conditions that firms

[4] See Liberti and Petersen (2017) for an insightful analysis of soft and hard information in the context of financial markets and financial intermediation institutions.

[5] Similarly, Garmaise and Moskowitz (2005), establish a link between the consolidation of the US banking institutions through mergers and acquisitions and the deterioration of the credit conditions, leading to a reduced economic development and an increase in crime rates.

that voluntarily switch to another bank, although the creditworthiness of firms who switch banks as the consequence of a branch disappearance is higher on average, as reflected by their lower rates of ex-post defaults. We complement their findings by documenting that firms whose branches shut down experience a credit reduction that explains the decline in their activity, which is partially mitigated for firms that manage to obtain credit through the same or via another banking institution.

We also contribute to a literature that highlights the role of local banks in alleviating firms' financial constraints. For instance, Berger, Bouwman, and Kim (2017) document that the presence of small community banks reduces the financial constraints of firms during financial crisis. Bolton et al. (2016) and Beck et al. (2018) document that relationship lenders help small and medium enterprises relieve their financial constraints during episodes of adverse economic conditions. Along these lines, our paper suggests that banking markets are far from frictionless, and that distant lenders do not constitute a perfect substitute for local banks.

3. DATA AND VARIABLES

In this paper, we use data for the Spanish economy from various sources. We obtain financial data for the universe of the Spanish SME's for the period 2007 to 2017 from SABI. We define SME's as those firms with at least 5,000 and at most 100 million euro in revenues in at least one of the years of our sample period, in which at least 25% of ownership is in the hands of a single individual. In addition to financial information, SABI also reports detailed information of each of the bank branches with which a company has a relationship every year. In order to determine which of these firm-branch relationships are due to outstanding loans, we cross our dataset with the database of the Spanish Credit Registry from the Bank of Spain, which contains all the loans granted to Spanish companies by Spanish banks. We use this data to determine which SME's are affected by the closings of one of their bank branches as dictated by the Memorandum of Understanding (MoU). We obtain information about the exact location of each of banks' branches and their period of activity from the Gu´ıa de la Banca, published by Maestre Ediban. This database provides the universe of the active bank branches during the period 2007 to 2017. The database also identifies branches that have been closed or integrated into another existing branch, and hence, it provides a complete picture of the openings and closings of Spanish bank branches over time. This information allows us to identify the closings of branches that occurred after 2012 in the non-core regions of banks. We can distinguish the MoU-related closings from other closings, i.e. closings of branches in core regions or closings of branches of healthy banks. We exclude the unrelated closings from our sample to avoid confounding effects. We cross the branch-level information data from Maestre Ediban with our database to identify which firms are affected by a branch closing and the exact moment in which they are affected. Since the data from SABI is sometimes incomplete, we require an exact match of all the credit relationships reported by firms in Sabi with the branch identifiers recorded in Maestre Ediban. In orther words, our sample includes only those firms for which we were able to identify all the reported bank relationships from Sabi with the recorded branch numbers from Maestre Ediban. Also, we include all the firms that had at least one credit relationship identified with the Spanish Credit Registry during our sample period. We end up with an unbalanced panel with a maximum of 409,748 observations and 48,207 firms. Of them, 1062 firms are affected by bank branch closings due to the MOU.

In order to understand the real effects of bank branch closings forced by the MoU on SME investment, activity, and survival, we use several variables that we describe in Table 1. The main dependent variables in our regressions are meant to capture the real effects on firms. To capture the effects on firms' probability of survival, we include the variable Exit, an indicator variable equal to one if the firm exits the industry the year of its exit. We capture firm investment in assets with the variable *Assets* and *Fixed Assets,* which are the amount of firms' total assets and that of fixed assets, respectively. We capture firm investment in human capital with the variable *Employees,* which is the raw number of firm employees. And we capture firms' activity with the variable *Sales,* which corresponds to firms' total sales, and *TFP* which is firms' total factor productivity as following the measure by Garicano et al. (2016). In order to capture the effect on credit, we measure firms' loan amount with the variable Credit which is the total amount of a firm's loan with a given bank. Our main independent variables are indicator variables capture the effect of MoUrelated branch closings. The variable *MoU* is equal to one the year in which the MoU took effect, and zero otherwise. The variable $MoU_{i,t=0 \text{ to } t=3}$ is equal one the year in which the MoU took place and the three years after that, and zero otherwise. The latter variable is meant to capture shortand mid-term effects of closings. Other independent variables that will be used in our regressions include *N. Branches,* which corresponds to firms' number of branches, *Multiple* banks which is an indicator variable equal to one if a firm has more than one bank relationship, and zero otherwise; and *Altman score* which is a firms' measure of closeness to financial distress defined as in Altman and Hotchkiss (2010).

Table 1 - Variable Definitions

Variable	Definition
Dependent variables	
Exit	Indicator variable equal to one the year in which a firm stops reporting activity, zero otherwise
Assets	Firms' Total Assets (in thousands)
Fixed Asseets	Firms' Property Plant and Equipment (in thousands)
Employees	Firms' number of employees
Sales	Firms' total sales (in thousands)
TFP	Firms' total factor productivity measured as in Garicano et al. (2016)
Credit	Firms' total loan amount with each bank (in thousands)
Inependent variables	
MoU	Indicator variable equal to one for the whole life of a company if the company has a loan from a bank branch that closes as a result of the MoU, zero otherwise
$MoU_{i,t=0 \text{ to } t=3}$	Indicator variable equal to one for firms affected by closings due to the MoU the year of the closing and the three years after, zero otherwise
N. Branches	Number of bank branches of a firm
Multiple banks	Indicator variable equal to one if a firm has multiple bank relationships, zero if a firm has only one bank
Altman Score	Firms' Altman z-score measured as in Altman and Hotchkiss (2010): Z-Score=6.56 x (Working Capital / Total Assets) + 3.26 x (Retained Earnings / Total Assets) + 6.72 x (EBIT / Total Assets) + 1.05 x (Book value of Equity / Total Assets).

In Table 2, we provide the summary statistics of the main variables used in our analysis.

As we can see, firms in our sample have, on average, a 2.8% chance of exiting the industry between 2007 and 2017. Firms have total assets for about 2.23 million euro on average, and firms' fixed assets amount to 0.9 million euro on average. Standard deviations of firms' assets are very large, which corresponds to the large variation in the size of SMEs. The number of employees in the average firm in our sample is 11. Firm sales are 1.97 million on average and total factor productivity is about 93. Also, SME's in our sample have an average amount of credit equal to 0.7 million euro with a large range of values between 6000 euro and 1.18 million euro.

Regarding our main explanatory variables, the mean of the variable *MoU* is 0.2%, which means that 0.2% of the observations, specifically around 820 observations, in our sample are affected by a MoU-related closing of a branch. The mean of the variable $MoU_{i,t=0\ to\ t=3}$ is 0.8%, which means that about 3,278 observations are affected by branch closings the year and up to three years after the branch closed due to the MoU. Moreover, the average number of bank branches with which a firm in our sample has a credit relationship is 1.21, ranging from 0 to 2. Finally, the average Altman z-score is 0.008.

Table 2 - Summary Statistics

	N. obs.	Mean	Std. Dev.	p10	p25	p50	p75	p90
Dependent variables								
Exit	409748	0,028	0,166	0	0	0	0	0
Assets	377382	2229,4	15175	142,66	334,16	772,27	1756,71	3830,75
Fixed Assets	349467	981,17	25716,67	15 51,96	190,98	585,64	1535,1	
Employees	320169	11,651	33,63	1	3	6	13	24
Sales	316249	1971,68	13987,96	115	321	863	1913	3876
TFP	262253	92,92	5139,1	22,039	34,983	51,8	74,74	107,92
Credits	273218	709,31	9356,5	6	34	153	470	1178
Independent variables								
MoU	409748	0,002	0,049	0	0	0	0	0
After 0-3 MoU	409748	0,008	0,091	0	0	0	0	0
N. Branches	409748	1,210	0,907	0	1	1	2	2
Altman z-score	409748	0,008	0,091	0	0	0	0	0

4. EMPIRICAL STRATEGY AND IDENTIFICATION

The purpose of our paper is twofold. First, we want to study the real effects of bank branch closings on firm outcomes. Second, we want to explore whether the effects on firms, if any, have an impact on the local economies. Specifically, at the microeconomic level, we want to test whether losing a credit relationship has an effect on the investment, activity, and survival of SMEs, and whether this effect is due to a credit reduction following the lost relationship. At the regional level, we want to test whether branch closings lead to a reallocation of credit within communities or if instead credit and economic activity are reallocated across communities in a way that some regions are benefited at the detriment of others increasing regional disparities.

The empirical challenge when testing these ideas is to find an exogenous source of variation to capture the effect of the credit supply shock. Indeed, if the reason why a firm stops receiving credit from a bank is because of changes in the firm's credit risk, then the causal effect of a credit supply shock cannot be identified. To address this concern, we use the Memorandum of Understanding (MoU) as an exogenous source of variation of credit supply. In June 2012, the Spanish banking sector requested external aid to recapitalize its banking sector and restore financial stability. The banking sector in Spain had been severely affected by the burst of the real estate and construction bubble, and the economic recession that followed. In the MoU, the EU conducted stress tests on Spanish banks to identify the most affected ones and provide recapitalization for them. In exchange, Spain would have to reorganize its banking system while complying with several strict measures dictated by the EU. One of these measures entailed, for each recapitalized bank, a drastic downsizing of its branch network. Specifically, for each recapitalized bank, the MoU distinguishes two regions: the core region, where the bank is headquartered and where it established its very first branches; and the non-core region, which are the rest of regions in Spain where the bank conducts business. The MoU-mandated downsizings forced banks to indiscriminately close all the branches in the non-core regions and it also obliged a significant reduction of the number of branches in the core regions. For example, for Caixa Catalunya, a bank originally from Catalonia, the bank was forced to close or sell its whole business outside of Catalonia, thus refocusing all of its activity in its core region where the number of branches also had to be reduced. Specifically, the official document of the restructuring plan for Caixa Catalunya establishes that "As part of its restructuring, the Bank will close and/or sell the whole business outside Catalonia, refocusing its activities in the core region. Furthermore, there will be additional branch and staff adjustments in the Catalan network and central services".[6] The list of banks affected by the MoU and their core regions can be found in Figure 1.

[6] Find the restructuring plan for Caixa Catalunya Bank in "EC. State Aid n° SA. 33735 (2012/N)

Figure 1 - Affected banks and core regions

Bank affected by the MoU	Core region of the bank
BFA/Bankia	Madrid, Valencia, Castellón, Alicante, Las Palmas, Santa Cruz de Tenerife, Ávila, Barcelona, Segovia, La Rioja, and capitals of province of non-core regions
Catalunya Caixa	Barcelona, Tarragona, Lleida, Girona
Nova Caixa Galicia	Coruña, Lugo, Ourense, Pontevedra, León, Asturias
Banco Valencia	Valencia
Banco CEISS	León, Palencia, Zamora, Valladolid, Salamanca, Ávila, Cáceres, Soria
Banco Caja3	Huesca, Zaragoza, Teruel, Badajoz, Burgos
Liberbank	Asturias, Cantabria, Badajoz, Cáceres, Guadalajara, Albacete, Ciudad Real, Cuenca, Toledo
Banco Mare Nostrum	Madrid, Baleares, Murcia, Granada, Almería, Málaga, Cádiz, Sevilla, Jaen, Huelva, Córdoba, Toledo, Ciudad Real, Guadalajara, Albacete, Cuenca, Alicante, Valencia, Castellón, Melilla, Las Palmas, Santa Cruz de Tenerife

We use the closings of bank branches of affected banks outside of the core region as an exogenous shock to the supply of credit to SME's. We consider treated firms as those that lost a credit relationship because they had an outstanding loan from a bank that was forced to close the branch under the MoU because the branch was operating outside the core region of the bank. We consider only those branches that were operating outside the core region of the bank because all branches in non-core regions had to close, irrespectively of their financial health. We compare the fate of these firms to firms that had outstanding credit relationships with banks that did not need recapitalization and their branches did not close. For instance, for the case of Caixa Catalunya Bank, we compare the future activity of firms that had a credit relationship with Caixa Catalunya Bank outside of Catalonia and lost this relationship because their branch closed, to the investment activity and survival of firms operating in the same region of the affected firm but whose credit relationships were with banks that were not affected by the MoU and that did not close their branches at all.

– Spain. Restructuring of Catalunya Banc S.A." here: https://ec.europa.eu/competition/stateaid/cases/242006/2420061284183342.pdf

We estimate the following difference-in-difference model:

$$y_{i,t} = \beta_1 MoU_{(i,t=0 \ to \ t=3)} + \lambda_i + \alpha_t + \varepsilon_{i,t}$$

where the dependent variable $y_{i,t}$ corresponds to one of our measures of investment, activity, and exit of a firm i operating at time t. We capture firms' likelihood of survival with an indicator variable that is equal to 1 if the firm exits the industry the year of its exit, and is equal to 0 otherwise.[7] We take the natural logarithm for the rest of our dependent variables, which capture firms' investments in physical and human capital as well as firm sales.

The main independent variable is $MoU_{i,p,t=0 \ to \ t=3}$, a dummy equal to 1 the year and up to three years after a firm experienced a branch closing due to the MoU. The coefficient of this variable, β_1, aims to capture the effect of the credit supply shock. In the baseline regressions, we include firm fixed effects to control for time-invariant unobserved heterogeneity at the firm level. Hence, as in any difference in difference model, our model allows for permanent differences across firms. We also include year fixed effects to allow for common yearly shocks that affect all firms in a given year. Errors are clustered at the firm, province, and industry level in all our regressions.

5. RESULTS

5.1. Baseline result: real effects

In this section, we present the estimation results of our difference-in-difference model presented above. First, we test the effect of the MoU by estimating the above model but including, as a dependent variable, the number of bank branches of SMEs. In this way, we are able to assess whether firms that had a credit relationship with a MoU bank outside the core region of the bank indeed lost their branch. In this specification, the coefficient β_1 captures the difference in the number of branches of affected firms after the MoU compared to before, relative to the same difference in the number of branches of firms in the control group. We report the results of this estimation in Table 3.

[7] This variable is put to missing the years after the firm exits the sample.

Table 3 - Change in the number of bank branches

MoU	-0.986*** (0.031)
FE	Firm, year
N	454,700
R2	0.171
Standard errors in parentheses, clustered at firm, province, and SIC level. * p<0.1, ** p<0.05, *** p<0.01	

As we can see, the coefficient is 0.99 and significant at the 1% level. Hence, affected firms lose on average 1 bank branch after the MoU compared to firms in the control group. This result suggests that affected firms are not able, on average, to replace the lost branch with another branch or a new bank. Hence, we can be confident that the MoU led to a significant reduction in the number of bank branches of affected firms.

We then test the real effects of branch closings on SMEs by estimating the difference-in-difference model above where the dependent variables correspond to our measures of investment, economic activity, and survival of SMEs. We estimate two versions of our difference-in-difference model. First, we estimate equation (1) to determine the average effect of branch closings on all firms. Then, we estimate a modified version of equation (1) where we interact our main variable of interest $MoU_{i,p,t=0 \text{ to } t=3}$ with the variable *Multiple,* which is a dummy equal to one if the company has credit relationships with more than one bank and it is equal to zero otherwise. We introduce this estimation because we expect the real effects of branch closings to be heterogeneous across firms. Indeed, it is possible that firms with more than one bank relationship suffer less from the negative consequences of losing a branch because they might be able to ask for more credit with one of their other banks. In contrast, the negative effects may be stronger for SMEs with a single bank relationship because, even though they may find other banks to borrow from, it may take time for these firms to start operating with a new bank. The modified version of the model in Equation (1) is a triple differences model as follows:

$$y_{i,t} = \beta_1 MoU_{(i,t=0 \text{ to } t=3)} + \beta_2 MoU_{(i,t=0 \text{ to } t=3)} \times Multiple + \lambda_i + \alpha_t + \varepsilon_{i,t}$$

We report the results of these tests in Table 4.

In Table 4, the dependent variables in columns (1) to (5) correspond to our variables of firms' probability of exiting the industry (column (1)), firms' investment in capital and labor (columns (2) to (4)), and firms' outcome in terms of sales (column (5)). The estimation results of Equation (1) are reported in Panel A and those of equation (2) in Panel B.

Table 4 - Baseline Result: Real effects

Panel A - All firms					
	Exit (1)	LnAssets (2)	LnEmployees (3)	LnFixedAssets (4)	LnSales (5)
$MoU_{0to3years}$	0.003 (0.003)	-0.074*** (0.017)	-0.065*** (0.025)	-0.090*** (0.024)	-0.122*** (0.036)
FE	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year
N	409,748	377,382	320,169	349,467	316,249
R2	0.254	0.919	0.874	0.900	0.847
Panel B - Single vs Multiple Bank Relationships					
	Exit (1)	LnAssets (2)	LnEmployees (3)	LnFixedAssets (4)	LnSales (5)
$MoU_{0to3years}$	0.010** (0.005)	-0.092*** (0.018)	-0.075*** (0.022)	-0.106*** (0.033)	-0.136*** (0.027)
$MoU_{0to3years}$ x Multiple	-0.016*** (0.005)	0.03575* (0.02105)	0.01940 (0.03293)	0.034 (0.032)	0.027 (0.058)
FE	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year
N	409,748	377,382	320,169	349,467	316,249
R2	0.254	0.919	0.874	0.900	0.847
Standard errors in parentheses, clustered at firm, province, and SIC level. * p<0.1, ** p<0.05, *** p<0.01					

In Table 4 - Panel A, the results of the estimations show that branch closings due to the MoU positively affect firms' probability of exit, although this effect is not significant. In contrast, branch closings cause significant reductions in the investment and operational activity of firms. In fact, to the extent that some of the firms exited the industry due to the credit shock, the observed negative effects occur on the surviving firms. First, firms' total assets experience an average decrease of about

7.4% over the three years following the shock. Also, it seems that a large part of the decline in total assets is due to reductions in fixed assets, which decrease by about 9%. In addition to cutting capital expenditures, SMEs experience significant reductions in labor, since the number of employees decreases by about 6.5%. These reductions in physical and human capital clearly have an effect on firm output, as sales decrease by about 12%. Overall, these results provide substantial evidence that, when SMEs lose one bank with which they had an outstanding loan or line of credit, they undertake drastic reductions in their investment in both assets and labor which in turn have an impact in their final revenues from sales.

In Table 4 - Panel B, we observe that there is a differential effect of branch closings for firms that lose their single bank relationship compared to firms that have multiple bank relationships and lose one. Specifically, the results show that firms that obtain credit from a single bank and their branch closes due to the MoU, experience a 1 percentage point increase in their probability of exiting the industry. This increase is significant at the 1% level and it represents an increase of 35% with respect to the unconditional mean probability of exit. In contrast, having multiple bank relationships seems to help firms insulate themselves from the negative effect of loosing one bank branch. For these firms, the probability of survival remains very similar to that of unaffected firms. The rest of columns in Table 4 - Panel B show that branch closings have a significant negative effect on firms' assets, employees, and sales, and that there are no significant differences between firms that have multiple bank relationships relative to firms with a unique bank.

5.2. Real effects: robustness

A key identification assumption in our estimations above is that of parallel trends. In words, the underlying assumption is that treated firms would not have evolved differently than control firms after the MoU had the MoU not taken place. In this section we explore potential threats to identification and conduct several analyses and robustness tests to address this concern. All the tables with the results of the tests in this section are relegated to the Appendix.

First, we test for parallel trends in the years prior to the MoU. The results of our parallel trends tests are reported in Table A1 of the Appendix. The variable $MoU_{(i,t=-3 \text{ to } t=-1)}$ captures the differences pre-treatment (i.e. 1 to 3 years before) between unaffected firms and firms that would lose a bank due to the MoU later on. The variable MoU year captures differences between affected and unaffected firms the year the branch closing occurred, and the variable $MoU_{(i,t=1\ to\ t)}$ captures differences between these firms up to 3 years after the implementation of the MoU. As we can see, firms in the treatment and control groups generally evolved in a similar way pre-treatment regarding our main variables of interest as significant differences appear, in all cases, only after the MoU took effect.[8]

Despite that there do not seem to be pre-trends in our dataset, the concern remains about whether treated and control firms would have evolved differently after the MoU had the MoU not taken place. This could be the case if, for example, the branches that were outside the core regions of banks had granted credit to firms that would have worse outcomes after the start of the downsizing prompted by the MoU, compared to firms operating with non-troubled banks. There are various reasons for why we could expect affected firms to have worse outcomes in the future. First, many of the banks' core regions included very large cities and capitals of large provinces and hence, it could be that when comparing affected and unaffected firms across regions our results are contaminated by a negative bias that is due to the economic level, population density, or other factors of non-core regions compared to core regions. To address this problem, we run our baseline model again but, in addition to including firm fixed effects, we include zip code interacted by year fixed effects. These fixed effects absorb any time-varying differences across core and non-core regions where these banks were operating thus allowing us to compare the outcomes of affected firms and unaffected firms operating in the same postal code in the same year. Second, firms operating in the real estate and construction industries are the ones that were expected to perform worse after the onset of the crisis. If MoU banks had disproportionately granted credit to firms in these sectors, the weaker balance sheets of these banks could be due to these worse performing firms. We address this concern by adding industry interacted by year fixed effects in our baseline model. In such a specification we are able to absorb time-varying changes across sectors and exploit variation that comes only from within sectors. The results of these estimations are included in Table A2 in the Appendix. As we can see, our baseline results remain quantitatively and qualitatively very similar similar when including these fixed effects.

[8] The number of observations in each regression in Table A1 is lower than those in the regressions of Table 3 because, in the parallel trends regressions, we restrict the sample to only those firms that have non-missing observations for all the years in our sample. When we run the parallel trends test with the unbalanced panel (untabulated), our results remain very similar to those reported.

To further address the concern that the troubled banks might have been more exposed to the construction and real estate sectors, we run our baseline model excluding those firms that were dedicated to these problematic sectors. The results of these estimations are reported in Table A3 in the Appendix. As we can see, the magnitude of the coefficient that captures the effect of the MoU generally decreases in all regressions with respect to the baseline specification, suggesting that firms in the real estate and construction sectors experience a decrease in their investment and performance. However, the coefficients remain economically and statistically significant in the new specification suggesting that our results are not completely driven by the outcomes of firms operating in the problematic sectors.

However, it could still be that firms not involved in the real estate and construction sectors that had obtained credit from MoU banks were worse than firms with outstanding loans from unaffected banks. Indeed, many of the banks that had to close branches in non-core regions due to the MoU were banks that resulted from mergers of the Spanish Cajas. The Spanish Cajas turned out to be the most vulnerable entities to the crisis for mainly two reasons. First, the Cajas had grown a lot in the previous years and they were oversized when the crisis hit. Second, even though these Cajas were similar to savings banks regarding their type of business, they had very different corporate governance and ownership structures that made them much less resilient to the crisis. For instance, Cajas did not have any equity and it was therefore impossible for them to resort to the stock market to raise capital (Mart´ın-Oliver et al., 2017; Bentolila et al., 2018). Hence, either due to their more aggressive growth in the previous years to the crisis or due to their poorer governance and ownership structures compared to banks, it is possible that the Cajas had granted credit to SME's that were worse than the credit granted to SMEs by unaffected banks and that is why the former had weaker balance sheets when the crisis started. If that is true, we should observe that banks that would later on become affected by the MoU had granted credit to worse firms than unaffected banks. We address this concern by running two additional tests. First, we run our baseline model excluding those branches that opened their business in the non-core regions after the year 2000. If it is true that, during the expansion period, the newly opened branches in non-core regions attracted clients at the detriment of their credit quality, then, including these observations in our estimations could be biasing our results downwards. Second, we study whether SME's characteristics determined branch closings due to the MoU. For that, we test whether the pre-existing characteristics of SMEs in our sample determine whether that firm is going to be part of the treatment group or not, that is, whether one of its bank branches is going to close in the near future due to the implementation of the MoU. We present the results of these tests in Tables A4 and A5 in the Appendix, respectively.

According to our estimation results in Table A4, excluding younger branches does not significantly change the coefficients from our baseline regressions. Also, as we can see in Table A5, firms' characteristics pre-treatment do not seem to determine their likelihood of being affected later on by a branch closing due to the MoU. These results were expected as they are consistent with the indiscriminate nature of the closings outside the core regions prompted by the MoU.

One could also argue that a better comparison group to compare to the treated firms would be one that includes firms that were working also with troubled banks but whose branches did not close. The firms in this group correspond to firms that have an outstanding loan from a branch operating in its core region that did not close. We also run a series of tests including this control group, in addition to, and instead of our baseline control group. The results of these estimations are reported in Table A6 in the Appendix. In Table A6, Panel A reports the results including both our baseline control group and also the firms operating with troubled banks that did not close their branches (i.e. in the core regions). Table A6 - Panel B reports the results where the control group corresponds to only those firms operating with non-closing branches in the core regions of restructured banks. As we can see, our results remain very similar to our baseline results. However, we do not use the latter control group in our baseline estimations due to the potentially endogenous nature of closings of branches in core regions. Indeed, in core regions, the MoU mandates that only a percentage of branches of each recapitalized bank must close, without specifying which ones, and hence, it is very likely that the ones that remain open are the best performing ones.

Finally, regarding the closings of bank branches, the conditionality agreement did not oblige banks to immediately close all bank branches in the non-core regions, but it allowed for the closings to happen gradually for a period of 5 years after the signature of the MoU. Even though we observe that most of the branch closings happened within the first 3 years (about 70% of them), we are concerned that the two-way fixed effects estimator gives biased results due to the potential hetero-geneous effects of branch closings across companies or over time (Chaisemartin and d'Haultfoeuille, 2020; Sun and Abraham, 2020; Goodman and Bacon, 2020). We test for negative weights using the estimator of Chaisemartin and d'Haultfoeuille (2020) and we find that very few groups have negative weights (only 0.11%) and that the sum of those weights is very small (-0.0003). We conclude the two-way fixed effects estimator provides robust estimates in our setting. Morevoer, if we use the multiple DID estimator by Chaisemartin and d'Haultfoeuille (2020), our results (untabulated) remain quantitatively and qualitatively very similar.

5.3. The credit channel

According to our previous results, SME's suffer from large negative effects after they lose a credit relationship. If the channel through which these negative effects occur is through credit, we should observe two things: first, affected firms should indeed be losing a branch relationship, which is what we saw in Table 3; and second, affected firms should see a reduction in their total amount of credit, at least in the short term, before they can replace the lost relationship, if at all, with a new one. This is what we explore in this section.

First we estimate our baseline difference-in-difference model (Equations (1) and (2)) where the dependent variable corresponds (the natural logarithm of) firms' total amount of credit. We report the results in Table 5.

Table 5 - Effect on Credit

	LnCredit (1)	LnCredit (2)
$MoU_{i,t=1 \text{ to } t=3 \text{ years}}$	-0.076** (0.038)	-0.115** (0.059)
$MoU_{i,t=1 \text{ to } t=3 \text{ years}}$ x Multiple banks		0.065 (0.062)
FE	Firm, Year	Firm, Year
N	273,218	273,218
R2	0.770	0.770
Standard errors in parentheses, clustered at firm level. * p<0.1, ** p<0.05, *** p<0.01		

The results reported in Table 5 indicate that firms lose, on average, about 7.6% of their total credit (Column (1)), and that this average effect is driven by firms that have a unique bank (Column (2)).

We also estimate our baseline difference-in-difference model with more granular data at the loan level. The advantage of using more granular data is that we can saturate our baseline model with a larger battery of fixed effects to capture unobserved heterogeneity. We include firm x year fixed effects to capture changes in the demand for credit by firms in a given year, in the style of Khwaja and Mian (2008), and we include bank x year fixed effects to control for changes in the supply of credit at the bank level. In this model, the coefficient of $MoU_{(i,t=0\ to\ t=3)}$ captures the change in the amount of credit given by the closed bank branch, relative to the amount of credit given to the same firm by other bank branches that did not close. Under the assumption that the amount of credit demanded by a given firm to its banks is homogeneous across all the firm's banks in a given year, this specification is robust to time-varying heterogeneity across firms. In other words, the results of this estimation are robust to potential violations of parallel trends. We report the results of our estimations in Table 6.

Table 6 - Loan level estimations

	LnCredit (1)	LnCredit (2)	LnCredit (3)
After $MoU_{0to3years}$	-0.246*** (0.063)	-0.297*** (0.065)	-0.373*** (0.120)
FE	Firm x Year, Bank	Firm x Year, Bank x Year	Firm x Year, Bank x Year
N	83,549	83,532	6,019
R2	0.676	0.680	0.716
Standard errors in parentheses, clustered at firm level. * p<0.1, ** p<0.05, *** p<0.01			

In Table 6, columns (1) and (2) include all affected and non-affected firms, and column (3) includes only affected firms. As we can see in columns (1) and (2), the amount of credit that firms receive from affected banks significantly decreases by about 25 to 30% relative to the amount of credit that the same firms receive from non-affected banks. In column (3), the control group does not include firms that have not been affected by the MoU. Instead, it takes into account only the firm-bank relationships of affected firms with unaffected banks. As we can see, the results remain significant at the 1% level and the economic effect is even larger.[9]

Overall, the previous results suggest that the contraction of the Spanish banking system, which involved the closings of almost half of the bank branches across the whole country had large negative consequences for SMEs. The results also suggest that the mechanism through which branch closings affected SMEs' activity, performance, and survival was a drastic reduction in the credit that they received from the closed bank branches. In the next section we verify whether the real effects on SMEs after branch closings indeed occur due to changes in their access to credit.

5.4. Instrumental Variables

In this section, we estimate an instrumental variables (IV) model where the main explanatory variable is firm' credit instrumented with bank branch closings due to the MoU. The dependent variables correspond to our usual measures of SMEs investment, sales, productivity, and survival.Specifically, we estimate the following IV model using two-stage least squares:

First Stage:

$$LnCredit_{i,t} = \beta_0 MoU_{t=0\ to\ t+3} + \delta_i + \gamma_t + \omega_{i,t}$$

Second Stage:

$$y_{i,t} = \beta_1 Ln\hat{C}redit_{i,t} + \lambda_i + \alpha_t + \varepsilon_{i,t}$$

The key identification assumption in the IV model is that the MoU, i.e. our instrument, affects firms' investment, sales, and probability of exit only through the credit channel. We believe that this assumption is plausible. The results of the IV estimations are reported in Table 7.

[9] We also run several tests (untabulated) to explore whether the reduction in credit of affected firms occurs beyond the three years after a branch closes. We find that this is not the case.

Table 7 - Instrumental Variables

	First Stage (1)	Exit (2)	LnAssets (3)	LnEmployees (4)	LnFixedAssets (5)	LnSales (6)
Credit		-0.06353*** (0.00953)	0.11908*** (0.03609)	0.40196*** (0.06126)	0.10384* (0.05323)	0.72902*** (0.08997)
After $MoU_{0to3years}$	-0.076** (0.038)					
FE	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year
N	273218	273218	256977	224114	240241	219955
Prob>F		0.000	0.001	0.000	0.051	0.000

Standard errors in parentheses, clustered at firm level.
* p<0.1, ** p<0.05, *** p<0.01

In Table 7, column (1) reports the results of the first stage regression and the rest of columns report the results of the second stage. Results indicate that reductions in SMEs' amount of credit due to MoU-related branch closings cause large and significant negative effects on firms' probability of survival, and on the investment and sales of surviving firms.

6. THE ROLE OF HARD AND SOFT INFORMATION

In a frictionless world, firms that lose a credit relationship should be able to replace it immediately by a new one and we should not observe any real effects on these firms' activity or performance. However, in the previous section we documented that the drastic credit reductions caused by the MoU translate into large significant negative effects on SMEs. In this section we explore whether firms try to avoid the negative effects of the credit supply shock by finding new credit relationships, and whether firms' ability to establish new relationships and attenuate the negative shock depends on their hard and soft information.

6.1. Hard information

We first study whether hard information helps firms to obtain credit. Indeed, in the recent decades, banks all over the world have taken advantage of technological change and big data to develop credit scoring systems to help them determine their clients' credit risk and the allocation of credit. These systems of credit scoring are based on firms' financial information like the information found in firms' financial statements and their past credit history. However, it is common for SMEs to have less financial information available than, for example, public firms, both because SMEs might be younger and hence they might not have a credit record, or because they do not keep the books systematically updated. Our hypothesis is that, if banks' credit scorings are mostly based on hard information, those SMEs with more or better hard information are going to be better able to overcome the negative supply shock.

To test this idea, we estimate a model where the dependent variable is equal to one if a firm obtains a loan (conditional on having applied for it) and zero otherwise. The explanatory variables in the model correspond to two proxies for the existence and quality of hard information, respectively. The first one, *Id(No Z-score),* is an indicator variable equal to one if firms do not have enough information reported in their annual accounts for us to be able to compute their z-score as defined in Table 1, and 0 otherwise. The second variable, *Z-score,* is a continuous variable equal to the value of the Z-score computed by ourselves, where we replace the Z-score by 0 for the companies for which the previous dummy variable is equal to one. We also interact these variables with our MoU variable, $MoU_{t=0 \text{ } to \text{ } t+3}$, to study the effect of hard information on credit for firms that lost a branch relationship due to the MoU. Our estimation includes firm and year fixed effects, and standard errors are clustered at firm, province, and sic-code level, as usual. We report the results in Table 8.

The results in Table 8 show that firms with no Z-score are 3.3 percentage points less likely to obtain a new loan (column (1)). In contrast, firms with higher Z-scores have a larger probability of obtaining a loan (column (1)), suggesting that hard information plays an important role in firms' ability to obtain new credit. In columns 2, 3 and 4 of Table 8 we study the effect of hard information on those firms that lost their branch due to the MoU.We observe that the MoU significantly reduced the ability of firms to obtain new loans, independently of whether these firms had hard information available or not (column (2)). However, in columns (3) and (4) the

Z-score continuous variable interacted with the MoU is positive and significant at least at the 5% level, which suggests that having higher Z-scores allowed firms to obtain new loans after being affected by the MoU. These results indicate that firms that have higher scores regarding their financial health were better able to insulate themselves after suffering from a negative credit supply shock due to the MoU.

Table 8 - Probability of obtaining a loan conditional on having applied

	(1)	(2)	(3)	(4)
Id(No Z-Score)	-0.033*** (0.007)	-0.036*** (0.007)		-0.033*** (0.007)
Z-Score	0.017*** (0.008)		0.028*** (0.009)	0.015** (0.007)
$MoU_{0to3years}$		-0.054*** (0.012)	-0.117*** (0.025)	-0.135*** (0.0.029)
Id(No Z-Score) x $MoU_{0to3years}$		-0.032 (0.032)		0.026 (0.038)
Z-Score x $MoU_{0to3years}$		0.105**	0.131*** (0.041)	(0.047)
FE	Firm, Year	Firm, Year	Firm, Year	Firm, Year
N	106,135	106,135	106,135	106,135
R2	0.353	0.354	0.353	0.354
Standard errors in parentheses, clustered at firm, province and SIC level. * p<0.1, ** p<0.05, *** p<0.01				

We also want to investigate whether the new loans obtained by firms with better credit scores came from the same bank or from establishing another relationship with a new bank. Hence, we test a model where the dependent variable corresponds to: i) an indicator variable equal to one if firms are able to keep the credit relationship with the same bank after being affected by a MoUinduced closing, and zero otherwise; ii) an indicator variable equal to one if firms are able to replace the credit relationship with another bank after losing their branch. The explanatory variables are our indicator variable *Id(No Z-score)* and the continuous variable *Z-score*. We estimate this model including only the firms that have been affected by the MoU. We include fixed effects at the sic code-year level and province-year level. We report the results of the estimations in Table 9.

Table 9 - Replace or maintain bank after branch closing

	Replace after close	Keep after close
Id(Z-score not reported)	-0.006 (0.008)	0.003 (0.004)
Z-score	0.025*** (0.005)	-0.001 (0.003)
FE	SIC code x Year, Province x Year	SIC code x Year, Province x Year
N	3,263	3.212
R2	0.153	0.141
Standard errors in parentheses, clustered at firm, province and SIC level. * p<0.1, ** p<0.05, *** p<0.01		

As we can see in Table 9, firms with higher Z-scores are more able to replace the lost branch by finding another bank (column (1)), suggesting, as before, that hard information plays an important role in firms' ability to obtain new credit. However, having more and better hard information does not seem to affect firms' ability to maintain their lost relationship with the same bank (column (2)).

If firms with better credit scores are more able to insulate themselves from the negative credit shock, we should observe that these firms suffer less from the negative consequences of the MoU. In Table 10 we report the results of our estimations on real effects presented in Section XX, but including, as explanatory variables, our main variable of interest, $MoU_{t=0\ to\ t+3}$, interacted with an indicator variable for whether firms are able to replace their lost branch with a new bank, or whether firms are able to maintain their relationship with the same bank after losing the bank branch. We present the results of these estimations in Table 10.

As we can see from Table 10, firms that were affected by closings due to the MoU and were not able to replace or keep their bank after losing their branch, have a significantly higher probability of exiting the industry and, conditional on surviving, firms have significantly lower investments in physical and human capital, and significantly lower sales. In contrast, firms that were able to replace the lost branch are more able to remain in business and also invest in more fixed assets. Hence, even though hard information did not play a significant role in helping firms maintain their bank after losing their branch, the results in table 10 indicate that firms that are able to maintain a credit relationship with their bank after the MoU are also able to mitigate or even eliminate the negative real effects caused by the MoU.

Table 10 - Real effects: Replace or maintain bank after branch closing

	Exit (1)	LnAssets (2)	LnEmployees (3)	LnFixedAssets (4)	LnSales (5)
Id(Close$_{i,t=0\ to\ t=3}$)	0.004*** (0.001)	-0.038*** (0.005)	-0.019*** (0.004)	-0.039*** (0.007)	-0.032*** (0.009)
Id(Close$_{i,t=0\ to\ t=3}$) x Id(Replace)	-0.013*** (0.003)	0.016 (0.025)	-0.011 (0.033)	0.093** (0.046)	0.064 (0.043)
Id(Close$_{i,t=0\ to\ t=3}$) x Id(Keep)	-0.005* (0.003)	0.041*** (0.013)	0.015 (0.014)	0.043** (0.021)	0.080*** (0.018)
FE	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year
N	532,252	490,794	419,138	409,177	416,574
R2	0.193	0.920	0.873	0.906	0.841

Standard errors in parentheses, clustered at firm, province and SIC level.
* p<0.1, ** p<0.05, *** p<0.01

6.2. Soft information

As argued in the previous section, SMEs might have less hard information available which leads banks to have to rely on more subjective and abstract information when allocating credit. Various papers have provided evidence of the role of soft information on credit allocation to firms (Berger et al. 2005, Liberti and Mian, 2009). In our setting, wee want to explore whether soft information helps SMEs establish new bank relationships and obtain credit after the MoU shock. Although soft information is very difficult to capture, some papers have used the distance between a client and the headquarters of its bank (Berger et al., 2005), or the hierarchical distance between the loan officer and her final boss as a proxy for soft information (Liberti and Mian, 2009). We adopt a similar strategy and take the geographical distance between the firm and the bank branch as our proxy for soft information. Our hypothesis is that, the shorter the distance between the client firm and the bank branch, the more the soft information that the loan officer can collect from the firm.

We take the closest surviving bank branch to each affected firm after its branch has been closed under the MoU. We build a dummy variable *Id(Near branch)* equal to one if the closest bank branch is less than 500 meters away from the firm, and zero otherwise; and another variable *Id(Num. Near Branches)* which is equal to the number of branches that are less than 500 meters away from the firm. We provide some summary statistics about these variables in Table 11.

Table 11 - Geographical distance - Summary statistics

Distance of closest branches (in Km)				
	Mean 1st branch	Std. Dev 1st branch	Mean 2nd branch	Std. Dev 2nd branch
MoU firms	0,614	1.127	0.866	1.492
Control firms	0.565	1.127	0.804	1.565
All firms	0.571	1.127	0.813	1.555
At least 1 branch is less than 500m away				
		Yes	No	Proportion of Yes
MoU firms		12,338	7,190	63.2%
Control firms		304,866	196,681	60.78%
All firms		317,204	203,871	60.87 %
N. branches within 500m				
	Mean	SD	Min	Max
Treated firms	2.446	2.264	0	5
Control firms	2.453	2.24	0	5

As we can see in Table 11, the closest bank branch for firms in our sample is just above 500 meters away. The closest bank branch for MoU firms is 614 meters away on average whereas for control firms the closest branch is 565 meters away. Also, 63% of MoU firms have at least one branch that is less than 500 meters away and this is also true for about 61% of the firms in the control group. Overall, these summary statistics suggest that firms affected by the MoU are not disproportionately located in banking deserts relative to control firms.

We test whether soft information, proxied by our distance measures, affects SMEs ability to replace the lost branch with a new bank or maintain its credit relationship with the bank that closed its branch. We also test whether soft information helps firms affected by the MoU mitigate their increased probability of going out of business due to the MoU. The results of these tests are reported in Table 12.

Table 12 - The effect of soft information

Panel A - Keep or replace the branch

	Keep after close (1)	Replace after close (2)
Id(NearBranch)	-0.016** (0.014)	0.013** (0.005)
FE	SIC code x Year, Province x Year	SIC code x Year, Province x Year
N	3,212	3,263
R2	0.145	0.151

Panel B - Firms' probability of survival

	Exit (1)	Exit (2)	Exit (3)	Exit (4)
Id(Close$_{i,t=0 \text{ to } t=3}$)	0.011*** (0.003)	-0.007*** (0.002)	0.009*** (0.003)	-0.006*** (0.0016)
Id(Close$_{i,t=0 \text{ to } t=3}$) x Id(Nearbranch)	-0.008* (0.004)	0.004 (0.003)		
Id(Close$_{i,t=0 \text{ to } t=3}$) x Id(Singlebranch)		0.013** (0.005)		0.012** (0.006)
Id(Close$_{i,t=0 \text{ to } t=3}$) x Id(Singlebranch) x Id(Nearbranch)		-0.016** (0.007)		
Id(Close$_{i,t=0 \text{ to } t=3}$) x Ln(N.nearbranches)			-0.003* (0.002)	0.0012 (0.002)
Id(Close$_{i,t=0 \text{ to } t=3}$) x Id(Singlebranch) x Ln(N.nearbranches)				-0.008** (0.003)
FE	SIC code x Year, Province x Year	SIC code x Year, Province x Year		
N	521,075	409,941	521,075	409,941
R2	0.192	0.223	0.192	0.223

Standard errors in parentheses, clustered at firm, province and SIC level.
* p<0.1, ** p<0.05, *** p<0.01

In Table 12, panel A shows the results of the estimation of firms' probability of keeping or replacing the bank as a function of the distance between the firm and the nearest active bank branch. These regressions include only firms that lost their bank branch due to the MoU. Having a bank branch that is located less than 500 meters away increases firms' probability of keeping the relationship with their bank by 1.6 percentage points. More interestingly, having another branch that is located nearby increases firms' probability of replacing the lost branch by switching to another bank by 1.3 percentage points. Both estimates are significant at the 5% level. The latter result provides evidence that the substitution of local technology (based on soft information) for distant technology (based on hard information) is not immediate. Panel B of table 12 provides further support for this lack of substitution effect. Indeed, the results show that firms whose branch closed due to the MoU, that do not have a nearby branch, are between 0.6 and 1.1 percentage point more likely to exit the industry. This represents 21 to 39% increase with respect to the unconditional mean of exit. This increase is significantly mitigated for those firms that have a nearby branch.[10]

7. MICRO- AND MACRO-LEVEL IMPLICATIONS

As we have documented in the previous sections, the profound changes in the Spanish banking sector translated into substantial negative real effects on SMEs. As a result of the MoU, the SME exit rate increased significantly and surviving firms suffered from large credit reductions which led them to cut investments and sales.

However, it is not clear from the analysis above, whether the substantial injections of funds into the banking system led Spanish banks to allocate credit more (or less) efficiently and whether the reallocation of funds across firms had an impact at the local level. The purpose of this section is to introduce a discussion of these issues and explore the presence of potential efficiency improvements (or losses) both at the micro- and the macro-economic (regional) level.

[10] We have estimated the model in Panel B including as dependent variables our proxies for investment in physical and human capital and sales. In the estimated results (untabulated) none of the coefficients is significant.

7.1. Credit rationning or cleansing effects?

We first study whether banks allocate credit more efficiently after the MoU. There are several reasons why banks might be allocating capital inefficiently before the MoU. A relatively recent paper by Gopinath et al. (2017) documents an increase in the dispersion of the marginal revenue product of capital in Spain in the pre-crisis period between 1999 and 2007, which accelerated in the postcrisis period between 2008 and 2012. The authors also find that the increasing dispersion occurs because capital inflows are misallocated towards firms that have higher net worth but that are not necessarily more productive. A more extreme case of capital misallocation is zombie lending, which could have occurred in Spain before the MoU. Indeed, during the financial crisis there was a concern that banks in Spain were evergreening bad loans by rolling them over in order to avoid recognizing losses.[11] The academic literature on zombie lending suggests that there are mechanisms that might induce banks to reveal their bad loans (Bruche and Llobet, 2014) and that bank recapitalizations and close inspections might be some of these mechanisms (Giannetti and Simonov, 2013; Bonfim et al. 2021). In Spain, the MoU entailed a close inspection of the Spanish banks and a substantial recapitalization of troubled banks with the recognition of their toxic assets. Hence, our hypothesis is that it is less likely that banks continue to allocate credit inefficiently after the MoU. We test this hypothesis by estimating our difference-in-difference model of equation (1) where the dependent variable corresponds to firms' amount of credit and the main explanatory variable is our indicator variable $MoU_{(t=0\ to\ t+3)}$, equal to one for firms that lost one bank branch due to the MoU and zero otherwise. In the model, we interact our main independent variable with a proxy for intrinsic firm quality using firms' total factor productivity (TFP) calculated right before the MoU. Specifically, we compute TFP for each firm and year in the same way as Gopinath et al. (2017). Then, for each firm, we take the average of the three years preceding the MoU, i.e. 2009 to 2011, as a measure of firms' productivity before they were affected by the MoU. Our objective is to test whether there is heterogeneity in firms' allocation of credit depending on their level of productivity. In principle, if credit allocation is more efficient, we should observe that banks allocate more loans to more productive firms. We report the results of our estimations in Table 13.

[11] Zombie Buildings Shadow Spain's Economic Future. The Wall Street Journal. September 16, 2010.

Table 13 - Firms' quality and credit allocation

	lnCredit All firms (1)	lnCredit All firms (2)	lnCredit Low Z-score (3)	lnCredit Low Z-score (4)
Id(Close$_{i,t=0\ to\ t=3}$)	-0.172*** (0.037)	-0.209*** (0.042)	-0.122*** (0.038)	-0.086*** (0.066)
Id(Close$_{i,t=0\ to\ t=3}$) x Id(HighProd50th)	0.055 (0.058)		0.165 (0.131)	
Id(Close$_{i,t=0\ to\ t=3}$) x Id(LowProdv25th)		0.140* (0.080)		0.002 (0.129)
Id(Close$_{i,t=0\ to\ t=3}$) x Id(HighProdv75th)		0.105 (0.093)		0.061 (0.157)
N	278,976	278,976	72,061	72,061
FE	Firm, Year	Firm, Year	Firm, Year	Firm, Year
R2	0.885	0.885	0.896	0.896

Standard errors in parentheses, clustered at firm, province and SIC level.
* p<0.1, ** p<0.05, *** p<0.01

We use three different variables to measure differences in productivity. The variables *Id(Above*50th*), Id(Bottom*25th*),* and *Id(Top*25th*),* are indicator variables equal to one if a firm's productivity is above the median productivity of the firms in its industry, in the bottom 25th percentile of its industry, or in the top 25th percentile, respectively, and zero otherwise. In table 13, the specification in columns (1) and (3) include the first variable, and the specification in columns (2) and (4) include the other two variables. Moreover, we first test the model including all firms in our sample (columns (1) and (2)) and then we test it again including only the subsample of firms with low pre-MoU Z-Scores (columns (3) and (4)), i.e. firms with Z-scores in the bottom 25th percentile of the sample. We calculate pre-MoU Z-Scores as the average of firms' Z-scores the three years previous to the MoU, i.e. in the same way as we calculate pre-MoU TFP.

The results in columns (1) and (2) of Table 13 show that more productive firms that are affected by a branch closing due to the MoU are not significantly more likely to receive more credit than less productive firms. This result suggests that banks only take into account hard (and soft) information, as we saw in Section 4, but not firm productivity, to allocate credit. To the extent that hard (and soft) information are not perfectly correlated with TFP, it is possible that banks allocate credit to firms with high credit quality but low productivity. In a pair-wise correlation test between firms' Z-scores and TFP, we find that Z-score explains only about 11% of the total variation of TFP. Hence, high-productivity firms with low Z-scores might inefficiently receive too low credit. We test this conjecture in the specifications of columns (3) and (4) of Table 13, where we focus only on the sub-sample of firms with low Z-scores. The results show that banks do not distinguish between highly productive and less productive firms in this sub-sample, which further confirms that banks do not focus on TFP when deciding to allocate loans. Overall, these results are in line with the results in Gopinath et al. (2017) which suggest the presence of some efficiency loss. That is, similarly to the pre- and post-crisis period, after the recapitalization of the banking sector, banks seem to continue to focus their business on firms with higher credit quality which are not necessarily the most productive ones.[12]

The results in Table 13 also show that firms affected by branch closings that have low TFP receive significantly less credit compared to non-affected firms. Specifically, these firms receive between 17% and 21% less funds than non-affected firms. Also, among firms with low Z-scores, firms with low TFP receive between 12% and 8.6% less credit than non-affected firms. These results suggest that some of the credit reductions introduced by the MoU can be attributed to cleansing effects.

Given the above results, we test the overall effect of the MoU on firms' TFP. On the one hand, cleansing effects might improve the allocation of resources towards better firms which would increase TFP after the MoU. On the other hand, if firms do not grant credit to the most productive firms, but rather, to the ones with higher credit scores, firms' productivity might be reduced. We test the impact on firms' total factor productivity and provide the results in Table 14.

As we can see in Table 14, firms affected by the MoU experience, on average, a reduction in TFP. Therefore, according to the results, it seems that, on average, the effect of capital misallocation on TFP dominates the cleansing effect.

[12] We can think of two plausible reasons why banks focus on firms with larger credit scores. The first one is that banks might not have the ability to compute firms' total factor productivity. The second one is that, even if banks understand which firms are more productive, their objective is to grant loans to those firms that have more ability to repay, which are not necessarily the most productive ones.

Table 14 - Effects at the Micro-Level: Impact of branch closings on firm TFP

	TFP (1)	TFP (2)	TFP (3)	TFP (4)
$Id(Close_{i,t=-3\ to\ t=-1})$		0.016 (0.015)		
$Id(Close_{i,t=0\ to\ t=3})$	-0.053*** (0.016)	-0.062*** (0.021)	-0.065*** (0.020)	-0.064*** (0.018)
$Id(Close_{i,t=0\ to\ t=3}) \times Multiple$			0.024 (0.027)	
$Id(Close_{i,t=0\ to\ t=3}) \times Id(Keep,Replace)$				0.057** (0.027)
N	262,253	244,414	262,253	215,240
FE	Firm, Year	Firm, Year	Firm, Year	Firm, Year
R2	0.703	0.718	0.703	0.656

Standard errors in parentheses, clustered at firm, province and SIC level.
* p<0.1, ** p<0.05, *** p<0.01

7.2. Levelling up

The results in the previous sections show substantial credit reductions to firms that were affected by branch closings after the MoU. As a result, these firms experienced drastic reductions in activity and profitability, which come both from efficiency losses and cleansing effects.

The purpose of this section is to explore whether the contraction in the bank branch network resulted in reduced overall employment and income in the local communities that were affected the most by the MoU. If that is the case, then despite its objective of sanitizing the Spanish banking system, the MoU might have contributed to increasing inequality across regions in Spain.

We test these ideas at the municipality level. There are 8131 municipalities in Spain. We take those municipalities in which there are only two bank branches or less and we compare the income and unemployment of those municipalities that lose at least one branch due to the MoU, with those that lose none. We focus on these municipalities because we want to assess the effects on those areas that become financially deserted as a result of the MoU. The fact that we only consider municipalities with at most two branches also helps us provide a cleaner identification of the effects. We estimate the following difference in difference model:

$$y_{i,t} = \beta_1 Branchless_{(i,t=0\ to\ t=3)} + \beta_2 Branchless_{(i,after\ t=3)} + \lambda_i + \alpha_t + \varepsilon_{i,t}$$

where the main independent variables are: $Branchless_{(i,t=0\ to\ t=3)}$ is equal to one if the municipality becomes branchless due to the MoU between 2012 and 2015 and zero otherwise, and $Branchless_{(i,after\ t=3)}$ is equal to one if the municipality becomes branchless due to the MoU more than 3 years after the MoU took place. We study two dependent variables: *LnNetIncome* which corresponds to the natural logarithm of average income per person in the municipality and *Unemployment-Benefits* which is the proportion of unemployment benefits in the total amount of income received by households on average in each municipality. We take these variables from the Spanish National Institute of Statistics (INE) database for the years 2015 to 2019. Hence, our main coefficients capture medium- and long-term effects of branch closings due to the MoU on the variations in municipalities' income up until 2019. Our regressions also include province fixed effects to control for unobserved heterogeneity across provinces and year fixed effects to control for yearly shocks. We report the results in Table 15.

Table 15 - Effects at the Macro-Level: Levelling Up

	LnIncome (1)	Unempl. Benefits (2)
$Branchless_{(i,t=0\ to\ t=3)}$	-0.054* (0.030)	0.013*** (0.004)
$Branchless_{(i,after\ t=3)}$	0.104 (0.106)	0.002 (0.006)
FE	Province x Year	Province x Year
N	2382	2256
R2	0.655	0.729
Standard errors in parentheses, clustered at municipality level. * p<0.1, ** p<0.05, *** p<0.01		

The results in Table 15 show that, in those municipalities that become financial deserts after the MoU, income per capita decreases by 5%. This decrease is significant at the 10% level. Morevoer, the weight of unemployment benefits in these municipalities' income per capita increases by 1.3 percentage points, and this increase is significant at the 1% level. Hence, in financial deserts, average income per capita declines significantly and unemployment increases significantly compared to those areas where bank branches remain open. These results provide some suggestive evidence that, despite the potentially beneficial cleansing effects brought by the sanitizing of the Spanish banking system, such drastic reductions in the bank branch network may have unintended consequences that may increase regional disparities threatening any efforts or policies that aim towards levelling up.

8. CONCLUSION

In this paper we study the real effects of credit supply shocks at the firm and municipality level. We exploit exogenous changes in firms' availability of credit using the closings of bank branches that are due to the Memorandum of Understanding (MoU), a mandate that obliged some banks with strong recapitalization needs to close all their bank branches outside their core region of business.

We find that branch closings caused significant reductions in the amount of credit of affected firms. Specifically, credit to affected firms declined by around 25% on average. We find that this reduction in credit had large negative effects on firms' probability of survival and that, those who survived, experienced significant reductions in their investments in assets and human capital, in their sales, and in their productivity.

We also identify heterogeneous effects across firms by showing that firms with more hard and soft information were more able to replace the lost branch relationship with another bank or obtain a new branch relationship from the same bank that closed their branch. Firms that were able to replace or keep their bank suffered less from the negative shock in credit supply. We further uncover that banks do not necessarily allocate their credit to more productive firms after the MoU. Instead, banks supply more credit to those firms with more hard and soft information, which suggests that banks might focus on firms' ability to repay rather than focusing on firm productivity.

Finally, at the municipality level, we find that those municipalities that became branchless after the MoU experienced significant reductions in average income per capita and significant increases in the weight of unemployment benefits over the total household income. These findings provide some initial suggestive evidence that, despite the beneficial effects of the MoU to reinforce financial stability in Spain, such drastic contraction of the bank branch network may have had unintended consequences such as increasing regional disparities challenging any government efforts towards levelling up.

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10. APPENDIX

Table A1 - Real effects: Parallel Trends

	LnAssets (1)	LnEmployees (2)	LnFixedAssets (3)	LnSales (4)
$MoU_{i,t=-3\ to\ t=-1\ years}$	0.016 (0.015)	-0.009 (0.019)	0.031 (0.007)	0.000 (0.021)
MoU Year	-0.019 (0.023)	-0.037 (0.023)	-0.012 (0.028)	-0.024 (0.020)
$MoU_{i,t=1\ to\ t=3\ years}$	-0.048** (0.025)	-0.061** (0.026)	-0.097*** (0.031)	-0.090*** (0.036)
FE	Firm, Year	Firm, Year	Firm, Year	Firm, Year
N	322,943	278,993	297,290	291,175
R2	0.929	0.879	0.900	0.873
Standard errors in parentheses, clustered at firm, province, and SIC level. * p<0.1, ** p<0.05, *** p<0.01				

Table A2 - Real effects: Robustness adding fixed effects

	Exit (1)	LnAssets (2)	LnEmployees (3)	LnFixedAssets (4)	LnSales (5)
$MoU_{i,t=0\ to\ t=3\ years}$	0.000 (0.004)	-0.069** (0.017)	-0.054** (0.019)	-0.085** (0.024)	-0.089** (0.029)
Firm, Zip-Year, Ind-Year FE	Yes	Yes	Yes	Yes	Yes
N	409,724	377,360	320,142	349,433	316,237
R2	0.260	0.921	0.879	0.900	0.855
Standard errors in parentheses, clustered at firm, province, and SIC level. * p<0.1, ** p<0.05, *** p<0.01					

Table A3 - Real effects: Excluding real-estate and construction firms

	Exit (1)	LnAssets (2)	LnEmployees (3)	LnFixedAssets (4)	LnSales (5)
$MoU_{i,t=1\ to\ t=3\ years}$	0.000 (0.001)	-0.053*** (0.016)	-0.049** (0.024)	-0.092*** (0.026)	-0.080*** (0.028)
FE	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year
N	333,406	307,657	265,116	284,021	267,094
R2	0.250	0.918	0.885	0.898	0.867

Standard errors in parentheses, clustered at firm, province, and SIC level.
* p<0.1, ** p<0.05, *** p<0.01

Table A4 - Real effects: Excluding branches open after year 2000

	Exit (1)	LnAssets (2)	LnEmployees (3)	LnFixedAssets (4)	LnSales (5)
$MoU_{i,t=0\ to\ t=3\ years}$	0.003 (0.003)	-0.064*** (0.011)	-0.058** (0.027)	-0.087*** (0.025)	-0.118*** (0.031)
FE	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year
N	408,066	375,757	318,845	348,060	314,782
R2	0.154	0.907	0.866	0.886	0.825

Standard errors in parentheses, clustered at firm, province, and SIC level.
* p<0.1, ** p<0.05, *** p<0.01

Table A5 - Real effects: Robustness, determinants of affected firms

	(1)	(2)	(3)	(4)	(5)
Working Capital / Assets	-0.0007 (0.0022)	-0.0008 (0.0022)	-0.0009 (0.0022)	-0.0008 (0.0031)	
Retained Earnings / Assets		0.0021 (0.0070)	0.0031 (0.0095)	0.0031 (0.0095)	
EBITDA / Assets			-0.0012 (0.0089)	-0.0011 (0.0090)	
Capital / Assets				-0.0003 (0.0033)	
Z-score					0.0552 (0.0404)
Intercept	0.0221*** (0.0009)	0.0221*** (0.0009)	0.0222*** (0.0009)	0.0223*** (0.0012)	0.1033*** (0.0259)
FE	zip and sic	zip and sic	zip and sic	zip and sic	zip and sic
N	36,002	35,968	35,886	35,886	35,887

Standard errors in parentheses, clustered at firm, province, and SIC level.
* p<0.1, ** p<0.05, *** p<0.01

Table A6 - Real effects: Robustness with different control groups

Panel A - Control groups: no restruct. banks, non-closing branches of restruct. banks					
	Exit (1)	LnAssets (2)	LnEmployees (3)	LnFixedAssets (4)	LnSales (5)
$MoU_{0to3years}$	0.003 (0.003)	-0.074*** (0.017)	-0.065*** (0.025)	-0.090*** (0.024)	-0.122*** (0.036)
FE	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year
N	409,748	377,382	320,169	349,467	316,249
R2	0.254	0.919	0.874	0.900	0.847
Panel B - Control group: non-closing branches of restructuring banks					
	Exit (1)	LnAssets (2)	LnEmployees (3)	LnFixedAssets (4)	LnSales (5)
$MoU_{0to3years}$	0.002 (0.004)	-0.029* (0.017)	-0.026 (0.019)	-0.042* (0.023)	-0.077*** (0.029)
FE	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year
N	83,410	77,553	66,461	72,280	65,793
R2	0.246	0.939	0.884	0.914	0.865

Standard errors in parentheses, clustered at firm, province, and SIC level.
* p<0.1, ** p<0.05, *** p<0.01

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