Unconventional Monetary Policy and Bank Lending Relationships*

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Abstract

How to support private lending to firms in recessions is a major open policy question. This paper examines how banks adjust their firm lending portfolios in a downturn by exploiting an unexpected drop in the cost of funding bank loans to a subset of firms in France in 2012. This cost reduction in the midst of a credit crunch causes increases in eligible firms' bank debt, and reduces both defaults on their suppliers and downgrades of their credit ratings, providing causal evidence that targeted unconventional monetary policy can be an effective lever to increase private credit and reduce contagion of financial distress. The effect is almost entirely driven by firms with only a single bank relationship—a numerous and understudied group—and the positive loan supply shock we examine is transmitted to firms through banking relationships. We find that, for high quality firms only, banking relationships support additional lending during a credit crunch. We also provide suggestive evidence that single-bank firms were substantially more credit constrained than multi-bank firms.

JEL classification:

Keywords: Relationship Banking, SME finance, Unconventional Monetary Policy, Bank Lending, Small Business

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1 Introduction

"[The new ECB policy] will allow banks to use loans as collateral with the Eurosystem, thereby unfreezing a large portion of bank assets. It should also provide banks with an incentive to abstain from curtailing credit to the economy and to avoid fire-sales of other assets on their balance sheets. The goal of these measures is to ensure that households and firms – and especially small and medium-sized enterprises – will receive credit as effectively as possible under the current circumstances."

Mario Draghi, President of the ECB, December 15th, 2011

Banks play a central role in reducing the asymmetric information costs of lending to small and medium sized firms (SMEs), making the bank-firm relationship of crucial importance.[1] Nonetheless, SMEs have long complained that banks sharply reduce the availability of credit in bad times, pushing many such firms into distress. How to support private lending to SMEs in times of aggregate contractions, and how bank relationships mediate this lending, are crucial questions that remain unanswered.

This paper exploits a unique natural experiment – an unexpected drop in the cost faced by banks of funding loans to a subset of their clients – to uncover how banks adjust their firm lending portfolios, which firms are most affected by bank belt-tightening in crises, and how lending relationships serve to transmit (positive) bank shocks. The shock we examine is the introduction of the Additional Credit Claims (ACC) framework referred to in the quote from Mario Draghi above, as part of a package of unconventional policy from the European Central Bank (ECB) and the Banque de France (BdF) during the European Sovereign Debt crisis in late 2011. The ACC policy occurred at a time of major expansion in collateralized ECB lending to banks, and lowered collateral standards, thereby materially reducing the cost faced by banks of funding loans to a subset of firms. We report several novel findings.

Firstly, the fall in the cost of funding loans is rapidly transmitted into an increase in the amount of bank credit to SMEs, and, in the subsequent year, a corresponding drop in the likelihood of payment defaults to suppliers and credit rating downgrades. That is, a targeted policy lowering banks' cost of funding loans to firms in a crisis period causes an increase in credit supply to such firms – the aim of many existing policies of uncertain effectiveness – without distorting lending incentives and encouraging risk shifting, and this policy also causes a reduction in defaults on debts to suppliers and in rating downgrades. Importantly, this is after removing all bank-level capital or liquidity shocks (using bank-month fixed effects), so our results reflect the adjustments to credit made by banks within their loan portfolios, in response to a pure change in the cost of lending that affects some of their borrower firms and not others.

The effect is almost entirely driven by firms with only a single bank relationship, which are naturally more likely to have established a borrowing – as opposed to a transactional – rela-

[1]See for example Stiglitz and Weiss (1981), Fama (1985), Diamond (1991), and James (1987) on the role of banks in lending to small firms; Paravisini (2008), Khwaja and Mian (2008), and Jiménez et al. (2017) for evidence of difficulties faced by firms in replacing bank financing; Sharpe (1990), Rajan (1992), Petersen and Rajan (1995) and Petersen and Rajan (1994), and Berger and Udell (1995) for the early work on bank relationships.

tionship with their bank. Moreover, within single-bank firms, the effect is driven by those with stronger lending relationships. In short, the positive loan supply shock we examine is transmitted to firms via banking relationships. However, firms with weak observable characteristics, such as high leverage or low levels of tangible assets, do not seem to benefit from the ACC, even if they have a strong banking relationship. These findings are consistent with the Bolton et al. (2016) model of banking relationships, in which the key benefit of relationships is that they ensure continued lending during crisis periods, but only for high quality firms.

We also provide suggestive evidence that over 2011, in a period of stress for the financial system (the peak of the Eurozone Sovereign Debt Crisis), single-bank firms were substantially more credit constrained than firms with multiple bank relationships. This is potentially because adverse selection makes single-bank firms near captives of their banks in crises, and thus much more vulnerable to liquidity shocks affecting their lender.

Around the world, and especially in Europe, policies aiming to increase bank lending to firms (and especially SMEs) during downturns have been an area of major policy activism in recent years. For example, in 2012 the United Kingdom introduced the Funding for Lending Scheme, while the Eurosystem introduced the three-year Long Term Refinancing Operations (often called vLTROs) together with the ACC framework, and introduced Targeted Long-Term Refinancing Operations in 2014.[2] However, the existing literature indicates that most schemes to provide additional liquidity to banks in times of financial stress are not transmitted to firms for a variety of reasons, such as liquidity hoarding by banks (e.g. Allen et al., 2009; Caballero and Krishnamurthy, 2008), or because (anticipated) fire sales of financial assets or other banking activities crowd out lending to firms (Diamond and Rajan, 2011; Abbassi et al., 2016; Chakraborty et al., 2016), particularly to small firms. Indeed, central-bank-supplied liquidity has been largely ineffective at expanding lending to firms (e.g., Iyer et al., 2014; Acharya et al., 2015), or only of benefit to the largest firms (e.g., Andrade et al., 2015; Rodnyansky and Darmouni, 2016). By contrast, our results indicate that providing liquidity to banks that is collateralized by bank loans to firms is an effective policy lever to induce bank credit expansion to SMEs in crises.

To our knowledge we are the first to provide clear evidence regarding a policy that generates a SME credit expansion in a crisis period, and in particular, cleanly identified evidence on which borrowers receive additional bank credit when banks expand their lending portfolios in bad times, and how lending relationships mediate these changes. We also provide novel evidence suggesting that firms with only one bank relationship are particularly affected by bank credit contractions, highlighting a disadvantage to the archetypal close banking relationship that only manifests in crisis periods.

The shock that we exploit was announced in December 2011 and implemented in February 2012, and consists in a major expansion in the availability of collateralized long term lending to banks by the ECB - the vLTROs - together with a reduction of one notch in the the minimum

[2]The Targeted Long-Term Refinancing Operations allowed banks to borrow from the ECB up to 7% of the value of their loans to companies and individuals (excluding mortgages). The Bank of Japan implemented a similar policy to the ACC in 2009 and 2010.

borrower credit rating required for a bank loan to be eligible as collateral. This created a shock with clear "treatment" and "control" groups for a difference in differences research design: firms in the credit ratings on either side of the new eligibility threshold. The groups are closely comparable and have very clear common trends in ex ante credit growth.

Thus, the natural experiment we examine operates at the firm-credit rating level, allowing us to examine the effects of a change in the cost of bank funds on lending for all French SMEs in the affected credit rating categories, and within the same bank and month. By contrast, the influential literature on shocks to bank liquidity largely excludes firms with only one bank relationship from their sample for econometric reasons.[3] This is not a minor exclusion: while single-bank firms are smaller than multi-bank firms, they make up a large fraction of the firm population (for example, about 83% of firms in France)[4], employ a large part of the workforce (about 38% of private sector workforce in France), and are younger (a median age of 14 versus 19 years) (See figure 1). Understanding credit access for such firms in bad times is crucial to our comprehension of changes in productivity and economic activity more broadly (e.g. Decker et al., 2014; Ates and Saffie, 2016).

[Insert Figure 1 about here]

However, we should expect the ACC shock to have a different effect on multi-bank firms than on single-bank firms, because single-bank firms are unavoidably exposed to any shock affecting their lender, and thus more likely to be constrained in a crisis period, given the difficulty of quickly establishing a new bank relationship (Darmouni, 2016). Moreover, the banks of single-bank firms have hold-up power over their borrowers, especially during crises, and so may charge higher rates (Santos and Winton, 2008) or instead choose to protect these rents for the future by providing additional funding in these periods (Bolton et al., 2016).[5] Which of these effects dominates is an empirical question.

One of our central results is precisely that only the firms that are largely ignored in the bank supply-shock literature – that is, firms with only one bank relationship – receive substantial

[3]Namely, use of the within-firm estimator to control for heterogeneous firm demand, together with a bank-level shock to provide identification. For example, see Gan (2007), Schnabl (2012), and Iyer et al. (2014). Khwaja and Mian (2008) are an exception: their main results focus on firms with more than one bank but they also consider the effects of their bank shock on all firms, arguing that those estimates are a lower bound on the real effects. Paravisini (2008) also examines a sample that includes single-bank firms, but finds larger lending effects for firms with multiple banks, and cautions that his results are for normal times, as opposed to a crisis period. A potential problem that is not resolved by the within-firm estimator is that banks might have heterogeneous responses to shocks which are correlated with the bank shocks themselves (see, for example, Khwaja and Mian, 2008); in our setting we have treatment and control groups within each bank-month, so this is not a concern.

[4]In 2008, 83% of the population of French firms had a single-bank relationship. This number is highly correlated with firm size: 86% of micro firms, 39% of SMEs and 21% of large firms had only one bank relationship (Aleksanyan et al., 2010).

[5]The literature provides some support for looking separately at single-bank firms. In the Detragiache et al. (2000) model, firms choose between two regimes: single or multiple banking, largely based on the probability of a bank liquidity shock which causes premature liquidation. Petersen and Rajan (1994) report that in the cross section additional bank relationships are associated with higher interest rates and lower credit availability, and that strong relationships may provide an informational monopoly, so that cost reductions are not passed on to the firm but instead manifest as quantity changes (p35). Houston and James (1996) also find differences in debt behavior between single and multi-bank firms in a sample of public firms.

additional credit as a result of the fall in the cost of funds for lending. We find a 8% increase in debt for single-bank firms in comparison to only a 3% increase for multi-bank firms. To explore the intensive margin we examine firms with debt of at least five percent of total assets (Amiti and Weinstein, 2017), and find an increase in leverage of 1.4 percentage points for single-bank firms (∼6% of the mean), and 0.7 percentage points for multi-bank firms. Thus, the effects of the ACC shock on multi-bank firms as a group are much smaller than those for single-bank firms, and interestingly, the size of the effect falls as the number of bank relationships rises.[6]

The weakness of the overall effect for multi-bank firms leads us to focus mainly on single-bank firms. Not all single-bank firms are equally affected by the reduced cost of funding loans. Banks adjust their lending portfolio as existing loans mature, or as firms request credit, and our shock provides a window into this process. The banks of firms with a single-bank are particularly likely to have invested in the relationship, given the reduced scope for information externalities benefiting other banks, or strategic default behavior by borrowers. Thus, single-bank firms with a well-established banking relationship would be most likely to see their lending increase (see for example Petersen and Rajan, 1994). We find evidence that banks value soft information acquired in a banking relationship: firms which maintain a longer relationship and provide more information to their bank by engaging in a wider scope of transactions see their debt respond more to the ACC shock.

However, our results are not consistent with a simple story whereby the soft information generated through relationship lending is the dominant factor. Hard information also matters: the additional credit attributable to the ACC only flows, on average, to firms with strong observables, i.e. firms with lower leverage, with more collateral, older firms, and larger firms. We next consider whether richer relationships are a substitute for these observables by examining the credit response of banks to firms with long relationships, but weak observables. Essentially no additional credit flows to these firms in response to the ACC policy, suggesting that strong hard information is a necessary condition for credit increases.

Taken together, these results suggest banking relationships allow banks to generate information about changes in firms' creditworthiness through the business cycle, and to modify lending terms accordingly, broadly in line with the models of Rajan (1992) and Von Thadden (1995), and more specifically providing support for Bolton et al. (2016). The latter paper models relationship lending over the business cycle as providing continuation lending to firms in recessions that they would not otherwise receive, but only for high quality firms, here proxied for by firms with strong ex ante observables. [7]

A key prediction of the Bolton et al. (2016) model is that firms that rely on relationship lending are less likely to default in crises, despite potentially having higher baseline default risk.

[6]When a firm has multiple lenders information externalities may be so large that relationships are much less valuable (Rajan, 1992), and adjustments may occur more on the price than the quantity margin (Petersen and Rajan, 1994).

[7]Further support for the Bolton et al. (2016) model comes from the fact that a similar analysis for multi-bank firms, which naturally have weaker relationships because of the possibility of inadvertent bank cross-subsidy and strategic default by borrowers, shows no additional lending to firms with low interest coverage. Moreover, the additional credit attributable to the ACC grows smaller as the firm's number of bank relationships rises.

We perform an oblique test of this in our setting by considering whether the additional lending generated by the ACC is in fact "good lending," or if it is instead disproportionately likely to cause defaults ex post. More defaults would support an alternative interpretation of our results: that by using the ACC to exempt firms from stricter lending standards, banks were in fact engaging in loan "ever-greening" or "zombie lending". We examine this directly by running our difference in differences design on default on debt to suppliers. We find that such defaults fall by approximately two percent of annualized payables in the year following the shock. Further, firms' propensity to receive a severe credit rating downgrade is significantly lower than that of controls in the year after the shock. In sum, our results point to relatively good lending based on measures of creditworthiness and a lower rate of ex post default, supporting the view that the additional credit generated by the ACC and transmitted through banking relationships is a key benefit of relationship lending, and that this is not obviously detrimental to participating banks.

Finding that the fall in the cost of bank funds causally reduced defaults on suppliers suggests that bank belt-tightening in crises may itself induce defaults in borrowers that then propagates through their supplier networks. Moreover, it implies that an additional benefit of the ACC policy is to reduce contagion of financial distress, consistent with Boissay and Gropp (2013), who show credit constrained firms pass on adverse liquidity shocks by defaulting on their suppliers.

A final but important category of firms that we examine are young firms and high-growth firms. While imprecisely estimated, high growth firms see especially large increases in their debt (of around 10 to 15 percentage points) relative to ineligible high-growth firms, and the effect is present for both single and multi-bank borrowers. Because high growth firms generally have high credit demand, this differential effect provides evidence consistent with these firms being credit constrained ex ante.

So far we have focused on differences within the single-bank category across treatment and control groups, rather than comparing single-bank firms to those with multiple bank relationships. This is because firms with only one banking relationship are very likely to differ from those with multiple banks on unobservable dimensions as well as on observables. However, some comparison of the effects of the shock across these categories is warranted, with the caveat that we can no longer be confident that these differences are causal.

We find a striking difference in the time trends in bank lending to single versus multi-bank firms: the average debt outstanding of the former group falls consistently over the four year period we examine (2010-2013), while for multi-bank firms debt growth is stable or increasing, despite having identical credit ratings, suggesting banks are not rolling over the debt of single-bank firms in this period.[8] This is consistent with the model in Detragiache et al. (2000), which presents multiple bank relationships as an insurance mechanism against bank liquidity shocks.[9]

[8] Only 14% of single-bank firms see their debt grow by over ten percent month on month in the pre-period (2011) in comparison to 23% of multi-bank firms, which is consistent with single-bank firms being less likely to have their debt rolled over when it is nearing maturity.

[9] They model the firm's likelihood of choosing to have only one bank as increasing in profits, bank recovery rate after default, and the probability of an idiosyncratic bank liquidity shock – single-bank firms are forced to prematurely liquidate if their bank is hit by a shock.

Additional evidence points to single-bank firms being more credit constrained than firms with multiple bank relationships, although we again note that the evidence for this is suggestive, not causal. Single-bank firms' debt increases much more in response to the reduction in bank funding cost, as described earlier. Further, only 29% of single-bank firms have undrawn credit lines worth over five percent of their debt stock in 2011, while 50% of multi-bank firms have such lines.

If single-bank firms are indeed more credit constrained than multi-bank firms in bad times, this has implications both for policy and for the academic literature. Firstly, policies to induce bank lending to firms may be more effective if oriented towards them in bad times, especially given the potentially contagion-reducing effects (via reduced defaults on suppliers) reported here. Of course, it is unclear whether such policies are welfare enhancing overall, but they are consistently popular with policymakers, meaning they are likely to persist in future. Secondly, the view in the empirical literature on relationship banking that fewer and stronger relationships lead to better access, weakly lower prices and lower collateral requirements may need a caveat: having only one bank relationship may be disadvantageous in crisis periods, at least for relatively weak firms.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the natural experiment we examine, the ACC reform; Section 4 discusses the empirical challenges and the identification strategy; Section 5 reviews the data, and Section 6 the results. Section 7 concludes.

2 Related Literature

A recent stream of papers focusing on the role of relationship banks during recessions has found mixed evidence, with some papers finding a protective role for relationships, while others find limited effects or even the opposite. However, these papers cannot empirically distinguish the different dynamics of single-bank lending during recessions from that of multi-bank firms because of their data or empirical strategies. In an important paper Bolton et al. (2016) model relationship lending over the business cycle, and provide empirical predictions for which we find support, as described earlier. In their empirical section they find that relationship banks (which they identify as banks that are geographically close to their borrowers' headquarters) in Italy provide continuation financing for their borrowers in crisis periods, unlike transaction banks. However, for econometric reasons this study focuses exclusively on firms with more than one banking relationship.[10] Similarly, Deyoung et al. (2015), find that a small subset of relationship-focused US community banks increased their lending to SMEs during the financial crisis, unlike the majority of banks. But their data is aggregated at the bank level, and so presents an average across firms with all numbers of bank relationships.

In contrast to these results suggesting a positive role for relationships in crisis periods, Jiménez et al. (2017) find that Spanish banks are somewhat more likely to approve loan ap-

[10] Albertazzi and Marchetti (2010) and Sette and Gobbi (2015) find protective results and also focus exclusively on multi-bank borrowers.

plications from new borrowers when they had a working relationship with the borrower in the past, and they find no differential effect of lending relationship over the cycle. Further, Santos and Winton (2008) report that banks in recessions opportunistically raise interest rates by more than is justified by risk alone, exploiting the hold-up power generated by the relationship. However, their data is for large firms only: listed corporations and syndicated loan users that have ready access to non-bank finance, making it difficult to view their results as applying to SMEs.

Using loan applications data for *new* borrowers, Jiménez et al. (2017) compare the relative importance of the bank and firm lending channels over the cycle. They offer evidence that firm balance-sheet strength matters in both recessions and good times for building new lending relationships (extensive margin of the balance sheet channel), while we investigate the intensive margin. Our focus is on existing borrowers as opposed to new borrowers, because we examine how relationships mediate banks' loan portfolio adjustment decisions, and on how borrower characteristics (including balance sheet strength) drive differences in bank responses to a supply shock, conditional on the structure of information available to lenders (i.e. monopoly vs. the shared information of the multi-bank setting).

More generally, this paper relates to the vast literature on the bank-lending channel (Bernanke, 1983; Stein, 1998) which tracks the transmission of financial constraints on banks to their borrowers. Extensive evidence supports the view that banks pass on monetary policy tightening (Kashyap et al., 1993; Kashyap et al., 1994; Kashyap and Stein, 2000; Jiménez et al., 2012)[11] and unexpected liquidity shocks (Peek and Rosengren, 2000; Khwaja and Mian, 2008; Chava and Purnanandam, 2011; Schnabl, 2012) to their borrowers. Much less is known however about adjustments to positive liquidity shocks and in particular, of highest interest from a policy perspective, about how expansions work in periods of aggregate contraction, the focus of this paper.[12]

Van Bekkum et al. (2017) examine a relaxation of the ECB's collateral eligibility requirements for residential mortgage-backed securities (RMBS) in the Netherlands at the same time as the shock in this paper. They report that in response banks slightly reduce the interest rates on newly originated mortgages underlying the RMBS, and increase loan volumes much more. Mesonnier et al. (2017) examine the effects of the ACC policy on loan interest rates using survey data, and focus their analysis on the effects of bank heterogeneity. Like Van Bekkum et al. (2017), they find a robust but relatively small drop in new loan rates (of 7bp as compared to average lending rates in their sample of around 250bp) in response to the policy shock.

Finally, this paper also contributes to the literature on the real effects of the lending channel,

[11] Jiménez et al. (2012)analyze the extensive margin of lending with loan applications data and offer micro-based evidence of an operative bank-lending channel, which varies with the strength of bank balance sheet (capital and liquidity).

[12] Paravisini (2008) examines a lending program in Argentina to support lending to SMEs in poorer regions. The expansion in available external finance had a substantial positive effect on the credit supply of constrained banks, but cautions that the reported effects are for good times. For France, Andrade et al. (2015) find evidence that the ECB long-term refinancing operations (vLTROs) implemented by the ECB in 2011 and 2012 had a combined positive and significant impact on the overall net credit supply to large borrowers.

which analyses how firm level outcomes are affected by bank supply shocks.[13] To our knowledge we are the first to show how positive liquidity shocks in crisis periods create real benefits in the form of avoiding default spillovers to firm suppliers. Furthermore, our paper offers a way to look at those borrowers who are unable to undo the bank lending shocks: the smallest firms (Khwaja and Mian, 2008; Iyer et al., 2014).

3 The Additional Credit Claim Shock

3.1 The Additional Credit Claim framework in 2011

All borrowing by banks from the Eurosystem (such as open market operations, use of the marginal lending facility and intraday credit) requires banks to provide eligible collateral (Tamura and Tabakis, 2013), consisting of both marketable and non-marketable securities (such as bank loans to high credit quality firms, known as "credit claims").[14] Until December 2011, bank loans had to be rated 4+ or higher in the Banque de France's rating scale to be eligible as collateral.[15]

In response to a liquidity crisis in the Eurozone interbank funding market in 2011, and as part of a broader set of non-standard monetary policy measures to improve liquidity, the ECB announced on December 8th 2011 that National Central Banks would be allowed to accept additional credit claims (ACC) as collateral from borrowing banks, should they decide to do so. On February 9th 2012, the ECB approved the criteria proposed by seven national central banks, including the Banque de France, for the implementation of the ACC framework (see Bignon et al., 2016 for further details). This was the first public acknowledgement that the Banque de France had chosen to implement this, and also provided the crucial detail that it had chosen to lower the minimum eligible credit rating by only one notch, from 4+ to 4 (corresponding to a maximum probability of default of 1% at one year).[16]

[13] The literature typically finds that real economic activity such as firm investment and inventory decisions (Kashyap et al., 1993; Kashyap et al., 1994; Chava and Purnanandam, 2011), firm investment composition (Garicano and Steinwender, 2015), as well as firm employment decisions (Greenstone et al., 2014; Chodorow-Reich, 2014) are significantly negatively affected by tight monetary policy or exogenous negative shocks to credit supply.

[14] Collateral is pledged by a borrowing bank at a national central bank and enters a borrower-specific pool against which it can borrow from the Eurosystem. Collateral is not tied to a specific operation, and if an asset becomes ineligible (for example, as a result of a rating downgrade) the borrowing bank must remove it from the pool and replace it with eligible collateral. Further, since October 2008 no quantity restrictions apply to Eurosystem open market operations if the borrower provides sufficient collateral (known as "full allotment").

[15] The Banque de France assigns credit ratings to all French non-financial companies with a minimum turnover of €0.75 million and accounting statements. The rating reflects the overall assessment of firms' ability to meet their financial commitments over a three-year horizon, and is used as to select the loans that banks are allowed to use as collateral for their refinancing with the Eurosystem. Ratings are based on firms' accounting statements, as well as information on supplier/customer trade bill payment incidents, bank loans reported by credit institutions, and legal information, as well as other sources. Firms are broken down into the following classes by default probability: 3++ (safest), 3+, 3, 4+, 4, 5+, 5, 6, 7, 8, 9 and P (in bankruptcy). The Banque de France does not receive any payment from rated companies and always informs companies of their rating, although the rating is not public. Finally, the rating is reviewed at least yearly on receipt of firm financial statements, and whenever a significant new development is brought to the attention of the Banque de France. A rating of 4+ is equivalent to a long-term rating of BBB-/Baa3 from S&P/Moody's.

[16] The ACC is temporary, but has been extended to at least September 2018. For further information on eligi-

The ECB also implemented two "very long-term refinancing operations" (vLTROs) with 3 year maturities around this time. The first vLTRO took place on December 21st, 2011, before the implementation of the ACC framework; the second took place on February 29th, 2012, after the French ACC framework was approved.

3.2 Estimating the size of the ACC shock

Credit claims made up 36% of the €412.8 billion of collateral pledged with the Banque de France by 54 banks at the end of 2011 (see Table 12 in Appendix). In France, the ACC reform made available an *additional* pool of corporate credit claim collateral of about €90 billion (total outstanding amount of loans that became eligible in February 2012), which, according to Bignon et al. (2016) corresponds to a collateral shock for French banks of 4.8% to 15.1% of their drawn loans. [17]

[Insert Figure 3 about here]

One plausible estimate for the size of the fall in the cost of funding for French banks at the time the ACC program was launched is the spread between the cost of market debt for these banks, and the ECB main refinancing rate at which they could obtain loans using the newly eligible collateral.[18] Figure 3 illustrates how the cost of market debt, such as the one provided by Gilchrist and Mojon (2017), stood relative to the ECB's main refinancing operation (MRO) rate. The cost of market funding reached about 5.2% on average in the last quarter of 2011, whereas the main refinancing rate was 1% at the end of the year, so the spread was over 400 basis points. This is, of course, merely an approximation as there are several difficulties in estimating the true market cost of funding for French banks. Firstly, we do not know the maturity of the loans against which the ACC claims are pledged and this information is hard to obtain, as collateral is not tied to a specific operation. Secondly, the maturity at which banks can borrow from the Eurosystem ranges from three years (as in the second vLTRO which occurred around the time of the ACC introduction) to one week. The benchmark that we are using as the market borrowing rate is a weighted average of different bond maturities and hence, does not systematically coincide with the average maturity of the central bank liquidity counterparts. Thirdly, market rates reflect rates for partly unsecured lending, while the ECB refinancing rate is fully secured (albeit with collateral that cannot be used in any other contexts).

However, over the course of 2012 the market-debt–MRO spread fell in response to massive injections of liquidity by the ECB; by the end of 2012 it seems clear that the advantage of the

bility criteria for Additional Credit Claims see https://www.banque-france.fr/uploads/tx_bdfgrandesdates/2012-02-9-eligibility.pdf

[17]In practice, the use of the ACC was more limited for corporate credit claims (20% of pledged ACC loans for total of €9 billion after applying the haircut schedules specified in the French ACC framework) than it was for stand-alone residential mortgages made eligible at the same period. Haircuts vary from 17% to 65% depending on the characteristics of the loans. See : https://www.banque-france.fr/fileadmin/user_upload/banque_de_france/Eurosysteme_et_international/cp-20130718-bce-reexamine-son-dispositif-de-controle-des-risques.pdf

[18]Note that in troubled times, price in the overnight market such as EONIA may not be a good proxy for banks' cost of funding as interbank markets become dysfunctional (see for instance Frutos et al. (2016)).

ACC combined with a below-market-cost funding had largely disappeared. Thus, the shock we exploit lasts, at most, for ten months (February-December 2012).

4 Identification strategy

We investigate the causal effects of a positive credit supply shock on treated (ACC) firms, and on closely comparable non-treated firms to show how banks changed their lending to such firms during the crisis. While the collateral reform was not targeted at small firms in particular, we restrict our attention to SMEs so as to shed light on the availability of credit for the most opaque, and thus likely the most constrained firms. We focus especially on single-bank borrowers as they are entirely exposed to any liquidity shock to their bank (Detragiache et al., 2000; Amiti and Weinstein, 2017) and cannot offset it by accessing funds from other banks. Furthermore, lenders to single-bank firms have private information about the firm that is not observable by other banks, making the cost of switching to a new lender potentially very high, especially during crises (Darmouni, 2016). France provides an ideal setting for this study as it is a bank-centered economy, and SMEs themselves are typically bank dependent: in our sample less than 1% of firms have access to the bond markets so that they were not able to substitute bank debt by issuing non-bank debt.

4.1 Empirical design

As illustrated by Figure 4, our empirical strategy exploits the fact that, together with a major expansion in cheap collateralized lending to firms by the ECB (the vLTROs), the new collateral framework reduced the costs to banks of lending to some types of firms (those rated 4, also referred to as ACC firms) — by making loans to these firms eligible as ECB collateral— but not to others that are closely comparable (firms rated 5+, one notch below). Thus, the firms rated 5+, whose loans were ineligible as collateral, are our control group in a difference-in-differences research design for the impact of the program on various firm-level outcomes.

We do not use the 4+ and higher rated credit rating groups (eligible both before and after) as controls because they were simultaneously subject to a large positive shock to their value as collateral i.e., they were themselves "treated", and at a higher treatment intensity than the ACC loans. This is because the vLTROs in December 2011 and February 2012 induced a large increase in bank borrowing from the Eurosystem, which generated a corresponding (and ongoing) need for collateral accepted by the ECB. Loans to firms rated above 4 (the ACC level) were eligible as collateral for LTRO borrowing, had low haircuts (10 - 17.5% for short term loans) and low opportunity cost as collateral, making such loans more attractive to banks in the post period. Because the 4-rated loans in the ACC group had larger haircuts, higher-rated loans were, in fact, more attractive to banks than ACC loans, and as a result we see loans to higher rated firms increase by more, as can be seen in Figure 5.[19]

[19]Importantly, we remove the effect of potentially different vLTRO uptakes, (or different bank portfolio qualities and asset allocation strategies) by including a full set of bank-month fixed effects. These absorb all differences in means across banks each month, leaving only the within-bank variation to drive our results.

We estimate an Intention-To-Treat effect based on the rating of the firm as of December 2011; its rating makes a firm eligible or ineligible for treatment, but we cannot observe which firms are actually treated (i.e., whose loans are pledged as collateral). Self-selection by firms into eligibility can be ruled out because ratings are assigned by the Banque de France, as described above. However, the assignment of ratings may have changed after the ACC program was introduced (although officially there was no change in the criteria). For example, if it became more difficult to get a rating of 4 then our estimates might reflect the change in the quality of firms rated 4 instead of the effect of the program. To address this concern, and also because after February 2012 a firm's rating can be affected by enhanced or restricted access to extra credit, the composition of our treatment and control groups is based on firm ratings before the ACC date, namely in December 2011, the month in which the ACC program was announced, but at that point its specifics and the ECB approval were unknown.[20]

[Insert Figure 4 about here]

Our main empirical challenge is to isolate the credit supply effect of the ACC program from other potential supply effects, as well as credit demand and business cycle effects during a time of financial stress. To separate demand from supply effects, the literature on the bank lending channel typically looks at cross-sectional differences in bank lending responses to bank-level shocks to liquidity (e.g., Kashyap et al., 1994; Kashyap and Stein, 2000). Moreover, to control for unobservable differences in firm-level loan demand they restrict their attention to firms that have at least two bank relationships (Gan, 2007; Khwaja and Mian, 2008; Andrade et al., 2015; Schnabl, 2012). This means that the effects on SMEs, which generally have a single-banking relationship, have not been well established.

In contrast to the bank lending channel literature, our paper exploits a supply shock which varies at the firm-credit-rating level instead of at the bank level. This empirical strategy has several advantages. First, it means that the economic interpretation is more direct, because banks' response to the shock likely reflects their normal adjustment process to a change in the cost of funds in recession periods, rather than the more disordered reaction of banks to emergency conditions generated by large unexpected liquidity shocks. Second, the shock is not vulnerable to concerns raised by Khwaja and Mian (2008) and Paravisini (2008) regarding the within-firm estimator, especially the concern that there may be variation in banks' responses to liquidity shocks, and that this variation is correlated with the shock in some way. Third, we do not exclude single-bank firms, which have typically been ignored in the existing literature. Finally we can study firm-level outcomes (and not firm-cross-bank level) because our identification strategy does not rely on variations in shocks to the supply of bank credit within firms (the within-firm estimator). Focusing on the firm level is critical to assess whether and how lending shocks are transmitted to the economy. Indeed, loan level results can be misleading as the loan-level bank-lending channel can be undone by firm-level adjustments of multi-bank firms, which reallocate their borrowing portfolio across banks to take advantage of improved

[20] Results are robust to defining samples based on November 2011 or January 2012 firm credit rating.

terms of credit and reduce their interest burden without increasing liabilities overall (Jimenez et al., 2014).

[Insert Figure 5 about here]

4.2 Specification

We estimate a difference-in-differences model of the form :

$$g_{it} = \alpha_i + \beta ACC_i \times Post_t + Bank_{kt} + Ind_{jT} + \Gamma' X_{i,y-1} + \epsilon_{it}, \tag{1}$$

where i indexes firm, j indexes industry, k indexes bank (or main lender for multi-bank firms), t denotes time in months and T denotes quarters. $Bank_{kt}$ is a (main) bank–month fixed effect. $X_{i,y-1}$ are firm-level ln(total assets), tangible assets / total assets and profitability (EBITDA/total assets) at the end of the preceding fiscal year, winsorized at 0.5% and 99.5%, and defined relative to their 2011 average, as is the case for g_{it} (details are described below); results are not sensitive to this demeaning. We cluster standard errors at the firm level to address serial correlation; results are robust to clustering by bank-quarter (cf. table 14).

The sample is composed of all 4 rated firms (newly eligible borrowers or "ACC firms", i.e., treated firms) and of 5+ rated firms (the closest ineligible borrowers on the credit rating scale of the Banque de France) as rated in December 2011 (before the ACC policy shock) with available data in our administrative databases. The ACC_i indicator takes a value of one for any firm with a rating of 4 as of December 2011 and zero otherwise. $Post_t$ is equal to 1 in each month after February 2012. In our baseline specification, we drop observations in January and February 2012, the period between the ECB's announcement that national Central Banks were allowed to implement an ACC policy (December 2012), and when the Banque de France actually announced that it was implementing the policy and providing crucial implementation details (February 2012). Results are not sensitive to dropping these months. Our parameter of interest is β, the intent-to-treat (ITT) effect of the reduction in bank funding costs induced by the ACC on newly eligible borrowers.

Our main dependent variable g_{it} is the cumulative growth rate of the firm's outstanding debt, and is precisely defined below. We only observe monthly debt totals in our data, not new loans. To proxy for new debt we thus look at the change in debt. However, because a large portion of changes in debt is driven by periodic amortization, month-to-month growth rates can be very volatile. Instead we follow Amiti and Weinstein (2017) and use a cumulative growth measure relative to a base period, which they argue has superior properties to a natural log transformation. Specifically, we measure the firm-level growth rate of debt as follows:

$$g_{it} = \frac{\sum_L D_{iLt} - \overline{D}_{i2011}}{\overline{D}_{i2011}}$$

D_{iLt} is the outstanding amount of drawn debt (short-term plus long-term bank loans) in month

t for firm i borrowed from bank L. $\overline{D}_{i2011}$ is the 2011 average for firm i of its total outstanding bank debt, summed across all its banks $L_1, ..., L_n$. Results are robust to changing the pre-treatment base period we use (i.e. all of 2011) to 2010, or to the first or to the last semesters of 2011: the base period does not affect our results (cf. robustness table 14). To mitigate the effect of outliers and reduce the weight given to firms with low levels of debt in 2011 (and so have "lumpy" debt dynamics) we top-winsorize g_{it} at 2%.

To ensure that the results are not driven by firms with low levels of debt, and to explore the intensive margin of the effect we also examine leverage as a dependent variable, dropping firms with very low leverage. Following Amiti and Weinstein (2017), which reports that only firms with substantial bank leverage (over 14 percent of assets in their Japanese sample) are sensitive to lender supply shocks, we restrict this separate sample to firms with at least 5% leverage.

We include an extensive set of fixed effects: firm (α_i), bank–month ($Bank_{kt}$) and industry–quarter (Ind_{jT}). Firm fixed effects remove the average cross sectional differences in debt growth across firms, and so controls for unobserved, time-invariant firm characteristics that affect credit demand. Though risk or investment opportunities may vary over time, our estimation window is limited to two years, mitigating the impact of time varying firm-level factors, and we additionally include firm-level characteristics as controls. Furthermore, for fluctuation in demand to materially alter our estimates, one would have to believe that demand changes are occurring in a way that, after removing the effects of industry-quarter fluctuations, is systematically different across our rating groups.

Our unique shock, which varies at the firm credit rating level (as opposed to the more usual bank-level variation provided by shocks to banks), allows us to include a full set of bank–month fixed effects. These serve to absorb both observed and unobserved time-varying bank heterogeneity.[21] As a result, our specification compares debt growth for firms borrowing *from the same bank*, with credit ratings only *one notch apart*, *in the same month*, dramatically reducing the scope for confounding variation to affect our estimates.

As mentioned earlier, the implementation of the ACC reform was concurrent with vast new lending facilities supplied by the ECB to banks (the second vLTRO). As a result, at the beginning of our post-treatment period, the comparison of newly eligible (rating 4) versus non-eligible firms (rating 5+) captures the joint effect of the vLTRO and of the ACC. Crucially, bank-month fixed effects absorb any differences *between* banks in terms of vLTRO uptake or usage across clients, an endogenous choice by banks likely based on variables that are not observable to the econometrician, and thus which cannot be fully controlled for using existing data from bank balance sheets or supervisory data. Further, bank–month fixed effects also remove other bank credit supply shocks, such as differences in bank responses to the ECB announcement of outright monetary transactions (OMTs) in August 2012.[22]

We also take advantage of the richness of the firm data available at a monthly frequency

[21] For multi-bank firms the fixed effect is defined with respect to their main lender; the average share of debt from a firm's main bank is 74% in 2011 (cf. table 1, Panel B).

[22] Acharya et al. (2015) reports that the OMT program announcement improved bank health, and in turn that banks with improved health increased their credit supply to low quality borrowers, with bank sensitivity to the OMT announcement depending on exposure to the sovereign debt of Portugal, Spain and Greece.

in the French Credit Register to investigate the dynamics of the effect. We extend our sample period to the end of 2013 and estimate a new specification which adds the ACC indicator interacted with indicators for each month, except for the first quarter of our estimation period. We then estimate a β_t for each month, providing nosier but finer-grained estimates of the ACC effect over time:

$$g_{it} = \alpha_i + \sum_{t > \text{Apr 11}} \beta_t \mathbb{1}_{ACC_i} \times t + Bank_{kt} + Ind_{jT} + \Gamma' X_{i,y-1} + \epsilon_{it}. \quad (2)$$

4.3 Identification assumption: No differential trends unrelated to credit availability

We focus on the difference between newly eligible firms (ACC) and non eligible firms from the closest credit rating category (Rating 5+), in firm-level debt growth with respect to the pre-reform period. Our main identification assumption is that treated and untreated firms share similar trends and that their credit trends would have been identical in both treatment and control groups in the absence of the ACC. Figure 6 shows the average growth rate in debt for treated and untreated firms.

[Insert Figure 6 about here]

Control firms look very similar to treatment firms in terms of their debt growth rate prior to the reform. Treated and control groups follow parallel trends prior to the reform, and diverge around the time of the reform. The effect is more pronounced in the single-bank sample, as shown in the top panel of figure 7. We confirm the parallel trend assumption more rigorously in a regression setting (see Table 13), where we interact the treatment indicator with a time trend in the pre-treatment period. Results indicate that ACC firms do not show any evidence of a statistically significant differential pre-trend in debt growth, for single-bank as well as multi-bank firms, in the six-months before the reform. The further back in time we extend this test, the noisier it becomes, because 2011 was a period of substantial re-rating of firms in the French economy such that there was extensive mixing of treatment and control groups (which are defined in December 2011) towards the beginning of 2011. Nonetheless, in unreported results we extend the parallel trend regression tests to a year before December 2011 for single-bank firms without finding any evidence of pre-existing differential trends.

[Insert Figure 7 about here]

4.4 Identification challenges: Exogeneity of rating, mixing between treatment and control groups and attenuation bias

As mentioned above, assignment to treatment and control groups is based on firms' ratings as of December 2011. However, firm rating varies over time as firms are downgraded or upgraded. As a result we have some mixing between our treatment group and our control group both in the pre and post treatment periods. Looking at the frequency of rating downgrades and upgrades over time in the year after the ACC reform we show that this biases our results downwards.

[Insert Figure 8 about here]

As shown by top panel of Figure 8, after a year about 15% of firms that were initially rated 4 (ACC firms) have been downgraded at least once, making them ineligible for treatment – by retaining them in the treated group we underestimate our effect. Similarly, about 25% of 5+ rated firms were upgraded at least once over the year following the ACC (see bottom panel of Figure 8), making them eligible for treatment. By retaining them in the control group we again underestimate the effect of interest. The further we extend the estimation window from the ACC date (February 2012), the stronger will be the effect of this attenuation bias.

5 Data and Summary Statistics

5.1 Data description and sample composition

This study considers a sample of independent (one legal unit) Small and Medium Size Enterprises (SMEs).[23] For the sake of our identification strategy we restrict our attention to SMEs with a rating of 4 and 5+ on the internal rating scale of the Banque de France. The data spans a period of two years centered on the date of the shock, from March 2011 to February 2013. The level of observation in our data is a unique firm–month combination, for firms having some positive bank debt over the period. Our primary data sources are the French national credit register (monthly data on outstanding amount of bank credit), available at the Banque de France, the FIBEN individual company database (yearly financial statement data), and the FIBEN internal credit rating database of the Banque de France.

5.1.1 Firm-level Credit Rating

Rating data comes from FIBEN internal credit rating database of the Banque de France. [24] Credit ratings are used by commercial banks to evaluate whether a firm's bank debt is eligible to refinancing operations for Eurosystem monetary policy operations. The rating is an overall assessment of a company's ability to meet its financial commitments over a three-year horizon, based on its financial statements as well as on qualitative information. Rating information is updated on a daily basis, should an incident impact the firm's ability to meet its financial commitments, or on a yearly basis for the annual review, provided firm accounting information is made available to the Central Bank. For the purpose of this paper, we assign firms in our

[23] SMEs are defined by the French Law of Modernization of the Economy (LME) of 2008. SMEs are firms with less than 250 employees, an annual turnover of less than EUR 50 million and balance sheet assets totaling less than EUR 43 million.

[24] The French Central Bank attributes credit ratings to a large number of resident non-financial firms. Around 270,000 companies (of which over 4,700 groups assessed on the basis of their consolidated accounts) are rated in this manner. Financial products are not rated; ratings are not made available to the public.

treatment or control groups based on their rating in December 2011[25] and select firms with active credit ratings over the period of interest. [26] We require each borrower to have a December 2011 credit rating of either 4 (newly eligible to be pledged as collateral under the ACC, i.e., treated firms), or 5+ (closest rating category, one notch below, for non eligible firms, i.e., control firms). A rating of 4 corresponds to a 1% probability of default at a 1-year horizon. Firms in these three rating categories represent about 50% of the total sample of SMEs with an active credit rating as of December 2011, with 22.1% having a rating of 4 (ACC), and 12.6% a rating of 5+ (one notch below).

5.1.2 Firm accounting data

This study considers a sample of independent (one legal unit) SMEs.[27] Independent SMEs are identified using Banque de France available information on firm financial linkages (structure of ownership). We restrict our attention to independent SMEs to exclude effects coming from intra-firm liquidity flows between holdings and subsidiaries for firms belonging to a group. Accounting data comes from FIBEN, a Banque de France database, which is based on fiscal documents.[28] We exclude micro-firms from our sample as well as agriculture, financials, utilities and public sector firms.[29] We also eliminate firms with special legal status and only keep limited liability firms, i.e., SA and SARL, which make 97% of our selected SME sample. We drop firms with negative debt, negative or zero total assets and missing number of employees. We use firm size (log of total assets or number of employees), age, leverage, tangible investment rate and trade credit use as independent variables. All firm characteristics variables are winsorized at the 0.5^{th} and 99.5^{th} percentiles throughout the analysis.

5.1.3 Firm-bank credit data

We merge yearly financial statement data with individual credit data from the French national Central Credit Register (CCR) available at the Banque de France.[30] CCR covers extensively bank exposures to firms at the bank-firm level on a monthly basis.[31] Reporting statements are

[25] Results are robust to selecting control and treatment groups based on November 2011 or December 2011 ratings.

[26] We exclude firms with inactive ratings i.e. whose financial information has not been updated since 23 months or more.

[27] SMEs that do not belong to a group.

[28] FIBEN includes all French firms which sales at least equal to EUR 75,000. In 2004, FIBEN covered 80% of the firms with 20 to 500 employees, and 98% of those employing more than 500 employees.

[29] Under the LME definition micro-firms have less than 10 employees and sales and total assets not exceeding EUR 2 million.

[30] Financial intermediaries, including all resident credit institutions, investment firms, and other public institutions, have the legal obligation to report any risk exposure (e.g., credit claims) over EUR 25,000 on a corporate counterpart as defined by a legal unit and referenced by a national identification number (SIREN).

[31] "In practice, a significant methodological change regarding the scope of this reporting threshold happened in April 2012. Before this date, a bank had to report its bilateral exposures larger than EUR 25,000 as measured at the level of its local branches. After this date, a bank has to report any bilateral exposure that is greater than EUR 25,000 as measured at the level of the whole bank" Andrade et al. (2015). Following Andrade et al. (2015), we correct for this break by looking at the information available at the bank branch-firm level. We dropped all bilateral branch-firm links with a total exposure smaller than EUR 25,000 and then collapse this homogenized database at the bank-firm level.

not limited to bank loans, they include undrawn credit lines as well as guarantees, and specific operations (medium and long-term lease with purchase option, factoring, securitized loans).

We first collapse credit exposures at the level of banking groups (in French: GEA, for *groupe économique d'appartenance*) [32] to identify the main lender of each borrower. Main bank is the banking group whose average share of drawn credit to firm i is the largest among firm i's bank lenders in 2011.

Next we aggregate exposures across banks for a given firm since we are interested in the overall effect of the ACC policy, at the firm level, and not at the firm–bank level. Indeed firms with multiple bank relationship can react by adjusting their sources of financing in equilibrium so that firm–bank level effects are not informative of the aggregate lending channel (Jimenez et al., 2014).

We require banking groups to be present in the sample throughout the whole period so as to make sure they are not affected by bankruptcy, restructuring or merger. Finally, an implicit requirement of the difference-in-difference strategy is that firms are present in the pre and post period. We thus require firms to maintain a bank relationship from March 2011 to February 2013, i.e., one year before and one year after the ACC reform. We analyze changes in the growth rate of drawn credit at the firm–month level, over the period during which the firm has some positive bank credit liability.

5.1.4 Payment default data

The last database we use consists of individual payment default data on trade bills coming from the CIPE (*Centrale des Incidents de Paiement*) hosted by the Banque de France.[33]

This register collects all incidents, from the first euro, of payments on commercial paper that have been mediated by French banks and for the companies that are the subject of a credit rating.[34] Thus, for each incident, the database contains the defaulted company, the date of default, the bank in charge of transmitting the commercial paper, the amount and the default's reason. This last information is broken down into two broad categories: inability to pay and dispute. In this study, all motives are considered as indicative of a voluntary default with the exception of the disputed amount already paid and late claim.[35]

Our main default variable is constructed by dividing the monthly total of non-payment incidents, multiplied by 12 to reflect an annual rate, and then divided by the value of trade account payables from the firm's (annual) balance sheet.

[32] We use the word "bank" in the rest of the paper to refer to banking group (GEA) and will specify local branch if we refer to a finer level of granularity within lenders.

[33] This database was used in particular by (Barrot, 2016; Boissay and Gropp, 2013; Aghion et al., 2012) among others, and payment defaults have been shown to be negatively and significantly correlated with a firm's access to future loans (Aghion et al., 2012).

[34] After the default's occurrence, the bank in charge of the firm's account must declare the unpaid payment within a maximum of 4 days from the date of rejection.

[35] The results remain qualitatively unchanged when only inability to pay are considered.

5.2 Summary statistics

Table 1 presents descriptive statistics that compare treated (firms with a rating of 4) and control firms (firms with a rating of 5+) in the year prior to the reform (2011). Panel A and B show summary statistics for the overall sample while Panel C and D are restricted, respectively, to single-bank firms and multi-bank firms. *p*-values associated with a *t*-test of the difference in means between the treated group and the control group, with standard errors clustered at the firm level, are reported.

[Insert Table 1 about here]

5.2.1 Treatment and control firms

Overall SMEs in our sample are mature firms with an average age of 17 years and median total assets of about €2,300 thousand. The average firm employs around 20 employees, has about €470 thousand in drawn credit with a leverage ratio slightly above 20%. It has 2 bank relationships and the length of its lending relationship with its main lender is around 8 years. Bank loans are their main external financial resource (less than 1% of the firms in our sample has access to the bond market).

Treated firms are significantly different from control firms: they are a little bit older, they have less debt in absolute amount and are also less leveraged. Their cumulative growth rate in debt with respect 2011, and measured by g(Debt) as defined earlier, is not statistically different than the one of control firms. The monthly probability of payment default, the number of payment defaults occurring in a month, and the importance of monthly default relative to payables account are higher in the control group (5+ firms) than their equivalent in the treatment group (ACC firms). Similar relationships hold when comparing treated and control firms within the single-bank subsample or within the multi-bank subsample.

5.2.2 Single-bank and multi-bank firms

We define single-bank firms as firms borrowing from only one bank (banking group) in 2011. N-bank firms borrow from more than N-1 bank and from less or N banks on average in 2011. Within a banking group firms can borrow from several local branches. A single-bank firm can thus also have several local lenders (less than 10% do). A total of 23 banking groups or standalone banks appear in our sample in 2011 for single-bank firms and 34 banks are present in our multi-bank subsample. The distribution of these groups' market share of (drawn) corporate credit is very skewed to the left and 8 banks represent 96 % of drawn credit in 2011 in our sample.

Figure 9 shows that on average, contrary to SMEs borrowing from multiple lenders, single-bank SMEs experience a declining trend in their borrowings over the period of interest: the average amount of outstanding credit granted to single-bank borrowers is downward sloping while the trend is almost flat for 2-bank firms and positive for multi-bank firms with more than 2 lenders.

[Insert Figure 9 about here]

Panel B of Table 1 presents descriptive statistics that compare single-bank firms and multi-bank firms in 2011. About 40% of our sample is made of single-bank firms that are typically excluded from most research papers which use the within-firm estimator (e.g., Gan, 2007; Schnabl, 2012; Andrade et al., 2015) in multi-bank firm samples to disentangle between supply and demand effects.

The sample includes 3,049 single-bank firms and 5,192 multi-bank firms. Single-bank firms are significantly different from multi-bank firms in almost every observable dimensions but their proportion of ACC firms vs. 5+ firms. Single-bank firms are younger, smaller. and less leveraged. They default slightly less on payment to their suppliers and these payment default represent less as a share of payables account than their multi-bank counterparts. In 2010, their had an average amount of debt which was almost 15% higher than in 2011, while the same difference was around 5% for multi-bank firms. Single-bank firms were thus on average on a significantly stronger deleveraging trend than multi-bank firms, as illustrated by Figure 7 and Figure 9.

Single-bank characteristics as well as the fact they are on a much more negative credit time trend ex-ante suggest that single-bank firms could have been more credit constrained than their multi-bank counterparts during the 2010-2011 crisis. It could also reflect that they had a lower demand for credit maybe as a result of a higher beta with the economy and in this case we should not expect treated single-bank borrowers to react much to the ACC reform that creates new incentives to lend to ACC eligible borrowers. This makes single-bank firms sample especially interesting to show evidence of a potential difference in the allocation of credit by banks during the crisis between borrowers with different degree of information asymmetry and loan liquidity.

To understand how banks allocate their lending portfolio in times of crisis we compare the intensity of their response to the one of multi-bank firms and we explore heterogeneity in the response to the ACC shock within the single-bank sub-sample.

6 Results

6.1 Average impact of the ACC reform

Figure 6 shows the average growth in debt $\overline{g_{it}}$, for the whole sample of SMEs, from 2010 to 2014. Trends in $\overline{g_{it}}$ are very similar in the pre-period for ACC and 5+ firms and diverge in the post-period. Both rating categories display a positive effect in their growth in drawn debt concurrent with the timing of the ACC reform, but the effect is significantly stronger for ACC firms (newly eligible) than for 5+ firms (controls). The effect of the ACC, reflected in the widening gap between the curves, takes place over the twelve months after the ACC is implemented, which is consistent with the period of time over which access to ECB liquidity provides a funding cost advantage over the interbank market (cf. Figure 3).

Next we distinguish between single-bank and multi-bank borrowers. In the top panel of Figure 7, we plot the average of growth rate in debt $\overline{g_{it}}$, for treated and for control firms, from

2010 to 2014, in the subsample of single-bank firms only. The graph shows that the two groups follow parallel trends prior to the ACC reform. The difference between the green line (5+ firms, i.e., control firms) and the blue line (treated firms) widens after March 2012 while it is almost non-existent in the pre-period. This confirms that 5+ firms are similar to ACC firms in terms of their credit growth prior to the reform.

The bottom panel of Figure 7 illustrates the same effect of the ACC reform but in the subsample of multi-bank firms. While treated and control firm still show parallel trend before the ACC reform the effect of the ACC is much weaker in the post reform period, suggesting that single-bank borrowers might be driving the effect.

6.1.1 Main Empirical Results

Table 2 presents the results of the difference in differences estimation of the impact of the ACC framework (February 2012) on firm borrowings for the average firm. We find that the reform increased the volume of lending to newly eligible borrowers.

[Insert Table 2 about here]

We examine single-bank and multi-bank firms separately. For single-bank firms, in our baseline specification, the growth in debt relative to its level in 2011 is 8.7% higher for treated firms than for control firms in the year after the ACC reform. The stability of the coefficient of interest and its significance in all specifications (1) to (6), when we progressively saturate the model with different set of fixed effects (firm, bank-month, industry-quarter), helps address the concern that borrowers and lenders also differed along unobserved dimensions that are driving the effect.

In columns (7) and (8) we consider the whole sample of firms and estimate the effect of the ACC reform conditional on being a single-bank and conditional on the number of bank relationships. With the caveat that the interpretation is not causal in this setting, as the choice of the number of banks is endogenous to the firm, we confirm our previous results. Treated single-bank firms experienced a 5.3% higher credit growth than treated multi-bank firms (column 7) and the interaction effect between ACC and the number of bank relationships is significantly negative (column 8). These results support our assumption that single-bank firms were more rationed for bank loans than multi-bank firms in 2011.

Interestingly the Post*Single-bank coefficient is negative and significant, with a larger magnitude than the effect of the policy itself (close to 9.5%). It shows that the differential time-trends between single and multi bank firms are largely unaffected by a change in the cost of bank lending, suggesting a deeper difference in how these borrowers are viewed by banks, despite having identical credit ratings. It also suggests that single-bank firms were constrained and that in the post ACC period the economic decision faced by the bank is, in general, whether to roll over existing debt, rather than whether to finance new projects.

Finally, in columns (10) we turn to multi-bank firms and our dependent variable is the growth in debt drawn from the main lender only. The magnitude of the (weakly statistically significant) coefficient estimate (0,026) is close from the one estimated in the pooled sample (column (7)), and suggests that the multi-bank effect is almost entirely driven by the main bank. We can thus rule out that a weak effect for multi-bank firms is due to firm-level adjustments of their borrowing portfolio across banks.

We redo this empirical exercise on firm's leverage and find similar and significant results as shown in Table 3.

[Insert Table 3 about here]

6.1.2 The effect of the ACC reform over time

We then estimate the time dynamic of the effect around the event date, taking advantage of our rich monthly dataset. We estimate equation (2) and present the results for the coefficient estimates in figure 10.

[Insert Figure 10 about here]

Figure 10 shows that the effect of ACC starts to materialize in February 2012 with the largest intensity from May 2012 to August 2012, before fading out. Given that the collateralization and pledging process is highly automatized and quasi-immediate in France[36] , a rapid effect around the date the reform was adopted is expected. After August 2012, the combined effect of the vLTRO and of the announcement of Outright Monetary Transactions (OMT) by ECB's President Draghi contributed to alleviate interbank market tensions resulting in a decline in EURIBOR-OIS spreads.[37] We can reasonably assume that it made central bank funding relatively less attractive at that time and that the cost of funding advantage of the ACC disappears for banks of high enough quality to borrow in the interbank market. The effect is much weaker and barely significant for multi-bank borrowers.

Interestingly, a similar pattern can be drawn from our leverage measure as shown in Figure 11.

[Insert Figure 11 about here]

6.2 Bank allocation of lending and the use of information

Because of the weakness of the overall effect for multi-bank firms we focus on single-bank firms. Not all single-bank firms are equally affected by the reduced cost of funding loans. Banks adjust their lending portfolio as existing loans mature or as firms request credit. Our shock provides a window into this process. We analyze how the impact of the reform varies, within single-firms, with hard and soft information (Petersen, 2004) about the firm.

[36] "The Banque de France has implemented in 2002 a very efficient automated platform, called TRICP, for individual banks to report and pledge credit claims at a very low transaction cost. Banks' pools of private credit claims can therefore be adjusted easily and frequently, which implies that the implementation of the ACC in France faced very little, if any, technical impediments on the side of banks." (Mesonnier et al. (2017))

[37] "Conditionally on fiscal adjustments or precautionary programs enforcement by candidate countries, the ECB is allowed to trade in secondary sovereign bond markets with no ex ante quantitative limits". See Dubecq et al. (2016)for an analysis of the effects of Eurosystem unconventional monetary policy on the euro interbank market liquidity.

6.2.1 ACC effects conditional on Lending Relationships

In this part we investigate the role of relationship lending and of soft information in the transmission of the ACC supply shocks to single-bank borrowers. Note that single-bank borrowers are already the archetypal relationship borrowers in the sense that relationship intensity, as measured by the percentage of borrower's total lending by the bank, is maximal.

The literature suggests that the soft information channel should be especially relevant in the context of SMEs whose access to external finance is highly impaired by information asymmetry (Berger and Udell (1995) and Petersen and Rajan (1994)). The acquisition of soft information should mitigate information asymmetry and help borrowers' access to credit. By soft information we mean non-measurable, borrower-specific information that is acquired by the lender over time through repeated interactions with the firm (length of relationship) and across a range of different products (scope of relationship).

[Insert Table 4 about here]

The vast majority of firms in our sample have long bank relationships – the median single-bank firm has a lending relationship length of about 6 years[38] – so that the length of the lending relationship may not be a sufficiently discriminating characteristic. Thus we also use the scope of the lending relationship as another proxy for the soft information acquired via relationship lending. Our *Large Scope* variable is an indicator, which takes the value one if the firm has other interactions with the bank based on different types of financial services such as leasing, commercial paper or securitized loans. The results presented in table 4 show that treated firms with a longer relationship benefit significantly more from the ACC policy and are driving the overall effect (we use a 6-year cut-off to qualify a long relationship as this is the median relationship length in the single-bank sample. This is higher than standards in the literature that commonly uses 3 or 4 years e.g. Bhue et al. (2016)). The ACC effect conditional on having a wider-scope lending relationship is not significantly different. However, the combined effect of having a long and wide bank relationship magnifies the average effect of the policy by more than 10% (column 3), emphasizing the importance of the richness of the information set acquired on the quality of borrowers in loan granting decisions.

[Insert Table 5 about here]

We also verify that the effect on lending is not concentrated in short-term credit only. Table 5 shows that for the average firm the ACC effect mostly affects medium and long-term debt (col.1 and 2). Next we investigate whether the maturity of loans granted depends on banking relationships. In columns 3 to 6 we split our sample between firms for which the length of lending relationship is strictly below or higher the sample median (6 years). Consistent with the idea that soft information provides valuable information about the credit risk of the borrower,

[38]The average length of lending relationship may even be longer as our data is right-censored at 14 years. Indeed we cannot measure the length of the relationship before 1998.

loans granted to single-bank firms with longer lending relationship are long-term loans. On the contrary, firms with short lending relationships only get short-term credit through the ACC.

Overall we find evidence that banks value soft information acquired in a banking relationship and used it to discriminate across borrowers in their loan allocation process: firms which maintain a longer relationship and information intensive relationships by engaging in a wider scope of transactions with their bank see their debt respond more to the positive shock. Taken together, these results suggest banking relationships allow banks to generate information about changes in firms' creditworthiness through the business cycle, and to modify lending terms accordingly, broadly in line with the models of Rajan (1992) and Von Thadden (1995).

6.2.2 ACC effects conditional on Hard Information

By hard information we mean quantifiable information based on financial disclosures. Using loan applications data for new borrowers, Jiménez et al. (2017) offer evidence that firm balance-sheet strength matters in crisis time to build new lending relationships. We show that it matters in the intensive margin as well by analyzing how response to our positive supply shock is related to firm characteristics that proxy for (lack of) financial strength and degree of riskiness.

We rank firms based on leverage, tangibility of assets, trade credit use, age and size (number of employees) in 2011, prior to the reform. For each of these factors, we then create an indicator D that can be interpreted as signaling relatively higher risk borrowers based on hard information available to the bank. Specifically we successively look at high leverage firms ($D = 1$ for firms with average leverage ratio in 2011 above the sample median) ; firms with with low asset tangibility ($D = 1$ for firms with ratio of tangible assets to total assets in 2011 in the bottom quintile of the distribution) ; firms that are net users of trade credit ($D = 1$ for firms with 2011 ratio of (Receivables-Payables) over Total Assets below the sample median, which is close to 0); young firms ($D = 1$ if firm age is no greater than 5 year old in 2011) and small firms ($D = 1$ for firms with less than 10 employees in 2011).

The estimated equation is

$$\begin{aligned} g_{it} = \alpha_i + \beta_0 Post_t \times D_i + \beta_1 \mathbb{1}_{ACC_i} \times Post_t \\ + \beta_2 \mathbb{1}_{ACC_i} \times Post_t \times D_i + Bank_{kt} + Ind_{jT} + \Gamma' X_{i,y-1} + \epsilon_{it} \end{aligned} \tag{3}$$

Table 6 presents the triple difference estimates of the effect of the ACC reform on lending to firms conditional on our five proxies.

[Insert Table 6 about here]

Within single-bank firms we find that the additional credit attributable to the ACC only flows, on average, to firms with strong observables: firms with lower leverage, with collateral, older firms, and larger firms. Contrary to evidence for other European countries (Iyer et al. (2014)), we do not find evidence of evergreening or zombie lending to riskiest borrowers.

We next consider whether richer relationships are a substitute for hard information by examining the credit response of banks to firms with long relationships but weak observables. In table 7 we do a horse race between hard and soft information to test whether they are complement or substitutes by running equation (3) in the subsample of single-bank firms whose length of lending relationship is greater or equal than 6 years in 2011. We find that no additional credit flows to firms weak observables in response to the ACC, suggesting that good hard information is a necessary condition for credit increases.

[Insert Table 7 about here]

This result fits with the Bolton et al. (2016) model of relationship lending over the business cycle. Specifically relationship lending provides continuation lending to firms in recessions that they would not otherwise receive, but only for high quality firms, here proxied for by firms with strong ex-ante observables.

6.2.3 ACC effects on Gazelles

A final but important category of firms that we examine are young and high-growth firms, so called 'gazelles'. These firms play a critical role in job creation (Haltiwanger et al., 2013), which makes it particularly important from a policy point of view to know whether and to what extent a reduction in banks' cost of funding was channeled to them under the form of more credit availability.

Firms with highest sales growth are selected based on their growth rate in sales, in each of the years 2009, 2010 and 2011. We define gazelles either as firms with sales growth at least equal to 10% (columns 1 and 4 of table 8) in each of these three years or as firms in the top quintile of the sales growth distribution in each of these three years (columns 2 and 5 of table 8). While imprecisely estimated, high growth firms see especially large increases in their debt growth (of around 10 percentage points) relative to ineligible high-growth firms, and the effect is present for both single and multi-bank borrowers. Because high growth firms generally have high credit demand, this differential effect provides evidence consistent with these firms being credit constrained ex ante. However, young firms do not appear to benefit from the ACC (column 3).

[Insert Table 8 about here]

6.3 The effect of the ACC on downgrade and payment default

A key prediction of the Bolton et al. (2016) model is that firms that rely on relationship lending are less likely to default in crises, despite potentially having higher baseline default risk. In our setting, an oblique test of this is to consider whether the additional lending generated by the ACC is in fact "good lending", or if it is instead disproportionately likely to cause ex post defaults, which would support an alternative interpretation of our results: that by using the ACC to exempt firms from stricter lending standards (as proxied for by interest coverage), banks were in fact engaging in loan "ever-greening" or "zombie lending".

6.3.1 Downgrades

We first examine this directly by running our difference in differences design on firms' propensity to receive a severe credit rating downgrade in the year after the shock. We estimate the probability that a treated firm suffers a rating downgrade of two notches or more below its December 2011 rating. To this end we start the analysis in January 2012 and define our post-treatment period from June 2012 on. Table 9 estimates a linear probability model for the probability of severe downgrade and shows that the probability of such a downgrade is lower for treated firms than for control firms. The results are consistent with the liquidity insurance prediction of the Bolton model and do not provide support to a loan "ever-greening" story.

[Insert Table 9 about here]

6.3.2 Payment Defaults

Next we analyze the effects of the ACC reform (February 2012) on payment default of firms to their suppliers. A payment default is defined as a failure to pay a trade bill to a given supplier, in full and/or on time. To investigate the effect of the ACC shock on firm's vulnerability, we define a measure of payment default intensity as twelve time the monthly of defaulted bills expressed as a percentage of firm's payables account. We focus our attention to payment incidents triggered by insolvency issues (liquidation of the firm) or by liquidity shortages leading a firm to, totally or partially, miss a payment to one of its suppliers. We also include default motives such as contesting of bills, since the label is somewhat ambiguous and may often reflect non-payment for liquidity reasons.[39] Note that because our sample is composed of significantly high credit quality firms selected based on their credit ratings, payment defaults remain rare events.

As illustrated in Figure 12 related to single-bank firms, whether ACC or 5+ firms, the size of payment incidents have evolved somewhat steadily around mean over 2011. However, while the payment incidents have represented an increasing share of payables for the 5+ firms over the year following the policy shock, the ACC firms suffered in a lesser extent at the same time, suggesting that ACC firms may have made the most of the policy change to prevent difficulties. To test this proposition, we apply the reduced form (1) on this default variable.

[Insert Figure 12 about here]

[Insert Table 10 about here]

Columns (1)–(3) of Table 10 shows that the ACC shock reduces the relative size of payment default for single-bank firms, as compared to untreated firms.[40] Column (4) shows that there is no pre-trend as the effect is insignificant in the year prior to the reform. Expressed relative to payables accounts, payment incidents of firms that are eligible for the ACC framework decreased by 1.8 percentage point in the 18 months following the shock as compared to firms that are

[39] Restricting the payment default to payment incapacity only does not change the results significantly.

[40] As additional, but tentative, evidence, Table 18 provides results from count regressions that suggests a positive role of ACC shock also on the number of defaults.

not. This reduced size of default actually begins to have a detectable effect only six months following the shock, at which point the reduced magnitude of defaults is about 2.4 percentage point relative to ineligible firms. Once again, this results is robust to a test on parallel trends condition. In columns (5) and (6) we extend the period of estimation to the end of 2013 and find that the effect persists over time.

This set results give additional support to our assumption that single-bank firms had ex-ante liquidity constraints during the crisis and that a positive supply shock helped them alleviating it. From a policy perspective these findings matter as the benefits of the ACC supply shock go beyond directly treated firms and spillover to their suppliers. There could also be a multiplier effect for the treated firm as payment defaults have been shown to be negatively and significantly correlated with a firm's access to future loans (Aghion et al., 2012).

Overall, the finding that the fall in the cost of bank funds causally reduced defaults to suppliers suggests that bank belt tightening may itself induce defaults in borrowers that propagate through their supplier networks in crisis periods, in line with the findings of Boissay and Gropp (2013).

In sum, our results point to relatively good lending based on measures of ex post default and creditworthiness, supporting the view that the additional credit generated by the ACC and transmitted through banking relationships is a key benefit of relationship lending, and that this is not obviously detrimental to participating banks.

7 Conclusion

This paper provides cleanly identified micro-evidence on how banks adjust SME lending portfolios during a crisis, in response to a unique natural experiment: a drop in the cost of funding loans to a subset of their clients. We find evidence that the cost of funding commercial loans is effective as a policy lever to induce lending, and that bank relationships serve to transmit this positive bank shock. Moreover, we provide novel evidence of a causal relationship between increased bank credit and both reduced payment defaults to suppliers, and ex post credit rating downgrades, suggesting that the incremental lending is not being used to sustain "zombie" firms.

We examine how bank responses vary with the extent of the private information advantage they have about the quality of each borrower. We find that the effect of the supply shock is driven entirely by single-bank firms, and especially those firms with which the bank has a deeper lending relationship. Further, the ACC supply shock seems to be used by banks to spare borrowers from complying with a tightening of lending standards applied to other firms, and again this is especially true for firms with a better banking relationship. However, hard information still matters in lending: good observable characteristics of the borrower appear to be a necessary condition for credit in our data.

Our findings can be seen on two levels. Firstly, when hit by a positive supply shock, banks use the private information acquired during the relationship in conjunction with hard information to allocate the marginal dollar of lending to borrowers. Firm balance sheet strength matters for the transmission of shocks to banks and so do lending relationships. These findings are in line with the literature on the firm balance sheet channel (Jiménez et al., 2017) as well as the literature on the benefits of relationship lending (Petersen and Rajan, 1995).

We contribute to the literature by extending these results to the group of single-bank borrowers and by providing well-identified evidence that a key benefit of bank relationships is that they provide lending during crisis periods, but only to high-quality firms (Bolton et al., 2016) .

Secondly, we compare single-bank and multi-bank responses to the ACC shock and argue that the difference suggests that single-bank firms appear to be substantially more credit constrained: banks direct much more additional credit towards single-bank firms than towards multi-bank firms. While the results cannot be causally interpreted – having one or several lenders is an endogenous decision, the determinants of which are beyond the scope of this paper – we present additional evidence consistent with single-bank firms being ex-ante more financially constrained. However, the differential response of banks to the ACC shock according to the number of banks the firm has could also reflect a disadvantage of having multiple banks: each lender may become reluctant to lend in bad times because of the risk that they may be subsidizing other lenders.

Beyond the pure financing effect, the policy has positive spillovers through the supply chain via lower default rate on trade payment, potentially reducing contagion effects. Furthermore, there could also be dynamic multiplier effects for the treated firms, because the payment defaults we track have been shown to be negatively and significantly correlated with a firm's access to future loans (Aghion et al., 2012). Whether policies such as the ACC are welfare enhancing remains unclear for many reasons, not least because potential crowding out effects of the policy, and effects on investment or employment have yet to be explored.

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A Main Tables

Table 1

Summary Statistics

Panel A: Firm-level statistics (2011) – All firms

	ACC firms				5+ firms				Diff.
	Obs.	Mean	Median	St. dev.	Obs.	Mean	Median	St. dev.	*p*-val
Age (years)	62,275	21.38	19	15.18	36,520	17.69	14.00	14.72	0.000
Total Assets (thousands of Euros)	62,275	2,244	1,299	6,060	36,520	2,256	1,386	5,156	0.919
N. of Employ.	62,275	21.26	16	18.90	36,520	19.77	15	17.51	0.000
Bank debt (thousands of Euros)	62,275	389	176	712	36,520	606	277	938	0.000
Leverage	62,275	0.18	0.15	0.15	36,520	0.28	0.23	0.22	0.000
Short-term debt / Total debt	58,368	0.32	0.05	0.38	35,133	0.34	0.12	0.39	0.014
$g(Debt)$ in 2010	51,757	0.084	0.05	0.624	30,540	0.076	0.062	0.519	0.494
N. of bank relationships	62,275	1.98	2	1.17	36,520	2.08	2	1.31	0.001
Share of main lender (banking group)	62,275	0.80	0.92	0.25	36,520	0.82	0.97	0.23	0.000
Length of main bank relationship (years)	62,275	7.90	6.83	4.16	36,520	7.29	6.00	4.05	0.000
Default indicator	62,275	0.049	0.000	0.216	36,520	0.053	0.000	0.225	0.114
Default, count	62,275	0.075	0.000	0.484	36,520	0.109	0.000	1.185	0.025
Default as % of payables	62,275	0.012	0.000	0.292	36,520	0.020	0.000	0.237	0.001

Panel B: Firm-level statistics (2011) – Single-Bank vs Multibank firms

	Single-bank Firms				Multibank firms				Diff.
	Obs.	Mean	Median	St. dev.	Obs.	Mean	Median	St. dev.	*p*-val
Age (years)	36,550	17.57	14	14.35	62,245	21.45	19	15.37	0.000
Total Assets (thousands of Euros)	36,550	1,879	1,141	6,797	62,245	2,465	1,416	5,000	0.000
N. of Employ.	36,550	15.96	13	12.99	62,245	23.47	18	20.43	0.000
Bank debt (thousands of Euros)	36,550	450	160	732	62,245	480	235	849	0.093
Leverage	36,550	0.24	0.17	0.22	62,245	0.21	0.18	0.16	0.000
Short-term debt / Total debt	34,085	0.17	0.00	0.33	59,416	0.41	0.34	0.39	0.000
$g(Debt)$ in 2010	29,466	0.146	0.106	0.617	52,831	0.045	0.006	0.567	0.000
ACC	36,550	0.627	1	0.48	62,245	0.632	1	0.48	0.608
N. of bank relationships	36,550	1	1	0	62,245	2.61	2	1.19	0.000
Share of main lender (banking group)	36,550				62,245	0.74	0.76	0.23	
Length of main bank relationship (years)	36,550	7.33	6	4.03	62,245	7.88	7.00	4.17	0.000
Default indicator	36,550	0.045	0.000	0.208	62,245	0.054	0.000	0.226	0.001
Default, count	36,550	0.080	0.000	0.770	62,245	0.092	0.000	0.843	0.332
Default as % of payables	36,550	0.013	0.000	0.178	62,245	0.016	0.000	0.316	0.069

Note: In Panel A, ACC firms (credit rating of 4) are the group "treated" by the ACC shock (5,195 firms), and firms rated 5+ are the "control" group (3,046 firms, one notch below 4). Note that this panel does not separate firms by the number of bank relationships they have. Default refers to default on trade bills held by suppliers. A default on trade bills is defined as a failure to pay a trade bill to a given supplier, in full and/or on time, due to either inability to pay or dispute motive. The final column presents the p-value of a two-sided difference in means test, with standard errors clustered by firm. Panel B presents statistics in 2011 separately for single-bank firms (3,049) and multi-bank firms (5,192). Single-bank refers to firms with only one bank relationship throughout 2011. Multi-bank refers to firms with more than one bank relationship on average in 2011.

Table 1
(continued)

Panel C: Firm-level statistics (2011) – Single-Bank firms

	ACC firms				5+ firms				Diff.
	Obs.	Mean	Median	St. dev.	Obs.	Mean	Median	St. dev.	*p*-val
Age (years)	22,909	19.65	17	13.87	13,641	14.08	9	13.12	0.000
Total Assets (thousands of Euros)	22,909	1,822	1,034	8,132	13,641	1,975	1,417	3,569	0.472
N. of Employ.	22,909	16.79	13	13.51	13,641	14.57	12	11.93	0.000
Bank debt (thousands of Euros)	22,909	288	118	517	13,641	722	295	943	0.000
Leverage	22,909	0.18	0.13	0.16	13,641	0.34	0.29	0.25	0.000
Short-term debt / Total debt	21,032	0.18	0.00	0.34	13,641	0.16	0.00	0.31	0.019
$g(Debt)$ in 2010	18,574	0.152	0.117	0.668	10,892	0.136	0.095	0.518	0.427
Length of main bank relationship (in years)	22,909	7.76	6.58	4.06	13,641	6.60	5.42	3.87	0.001
Default indicator	22,909	0.045	0.000	0.207	13,641	0.046	0.000	0.209	0.820
Default, count	22,909	0.063	0.000	0.364	13,641	0.110	0.000	1.167	0.071
Default as % of payables	22,909	0.010	0.000	0.145	13,641	0.017	0.000	0.222	0.056

Panel D: Firm-level statistics (2011) – Multibank firms

	ACC firms				5+ firms				Diff.
	Obs.	Mean	Median	St. dev.	Obs.	Mean	Median	St. dev.	*p*-val
Age (years)	39,366	22.39	19	15.39	22,879	19.84	17	15.19	0.000
Total Assets (thousands of Euros)	39,366	2,489	1,449	4,412	22,879	2,424	1,375	5,897	0.674
N. of Employ.	39,366	23.83	18	20.97	22,879	22.85	17	19.45	0.089
Bank debt (thousands of Euros)	39,366	447	216	798	22,879	536	270	928	0.000
Leverage	39,366	0.19	0.16	0.15	22,080	0.25	0.21	0.18	0.000
Short-term debt / Total debt	37,336	0.39	0.30	0.39	22,879	0.25	0.21	0.18	0.000
$g(Debt)$ in 2010	33,183	0.046	0	0.668	19,648	0.043	0.05	0.516	0.834
N. of bank relationships	39,366	2.56	2	1.14	22,879	2.72	2	1.28	0.000
Share of main lender (banking group)	39,366	0.73	0.75	0.23	22,879	0.75	0.77	0.22	0.041
Length of main bank relationship (years)	39,366	7.98	7.08	4.21	22,879	7.70	6.75	4.10	0.019
Default indicator	39,366	0.052	0.000	0.221	22,879	0.058	0.000	0.233	0.069
Default, count	39,366	0.083	0.000	0.541	22,879	0.109	0.000	1.196	0.155
Default as % of payables	39,366	0.013	0.000	0.350	22,879	0.021	0.000	0.245	0.005

Note: In Panel C, single-bank refers to firms with only one bank relationship throughout 2011. ACC firms (credit rating of 4) are the "treated" group (1,911 firms), and firms rated 5+ are the "control" group (1,138 firms, one notch below 4) in our main difference-in-difference analysis. The final column presents the p-value of a two-sided difference in means test, with standard errors clustered by firm. In Panel D, multi-bank refers to firms with more than one bank relationship on average in 2011. There are 3,284 firms in the ACC group, and 1,908 in the control group.

Table 2

Effect of the ACC policy on Firm Debt

	Single-bank						All firms		Multibank
	(1) Firm,Time	(2) BankxTime	(3) IndxQuarter	(4) Covariates	(5) -	(6) -	(7) -	(8) -	(9) g(main)
ACC×post	0.1018***	0.0944***	0.0887***	0.0827***	0.0867***	0.0867***	0.0347**	0.1199***	0.0264*
	(0.0174)	(0.0174)	(0.0176)	(0.0178)	(0.0191)	(0.0191)	(0.0153)	(0.0370)	(0.0137)
Size (lag)				2.3680***	2.7864***	2.7878***	2.4648***	2.4885***	1.3842***
				(0.4785)	(0.5164)	(0.5165)	(0.2498)	(0.2492)	(0.2384)
Tangibility (lag)					-0.0045	-0.0045	0.0188	0.0183	0.1188***
					(0.0036)	(0.0036)	(0.0176)	(0.0176)	(0.0207)
Profitability (lag)						-0.0001	0.0003	0.0003	0.0008*
						(0.0004)	(0.0003)	(0.0003)	(0.0005)
ACC×post×SingleBank							0.0531**		
							(0.0244)		
post×SingleBank							-0.0952***		
							(0.0176)		
ACC×post×N Bank								-0.0622*	
								(0.0332)	
post×N Bank								0.0965***	
								(0.0239)	
Bank-Time FE		yes	yes	yes	yes	yes	yes	yes	yes
Industry-Qtr FE			yes	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
N of clusters (firms)	2973	2968	2968	2912	2671	2671	7445	7445	4767
Observations	63,131	63,041	63,041	61,423	55,997	55,997	157,695	157,695	101,007
R^2	0.41	0.42	0.42	0.42	0.43	0.43	0.41	0.41	0.38

Note: This table presents difference-in-difference (DID) estimates of the effect of the ACC policy on the growth in the total bank debt of SMEs. We estimate the following equation:

$$g_{it} = \alpha_i + \beta \mathbb{1}_{ACC_i} \times Post_t + Bank_{kt} + Ind_{jT} + \Gamma' X_{iy-1} + \epsilon_{it}$$

where i indexes firm, j indexes industry, k indexes bank (or main lender for multi-bank firms), t denotes time in months and T denotes quarters. The dependent variable is the cumulative growth rate in the outstanding amount of drawn credit, $g(Debt_{it})$ defined as $g_{it} = (D_{ikt} - \overline{D}_{i2011})/\overline{D}_{i2011}$, where $\overline{D}_{i2011}$ is the firm's average debt in 2011. α_i is a firm fixed effect; $Bank_{kt}$ is a (main) bank–month fixed effect; Ind_{jT} is an industry-quarter fixed effect. The sample consists of all 4-rated firms (newly eligible borrowers or "ACC firms", i.e., treated firms) and 5+ rated firms (closest ineligible borrowers on the internal Credit Risk Rating scale of the Banque de France) as rated in December 2011 that meet the data requirements detailed in the text. The $\mathbb{1}_{ACC_i}$ indicator takes a value of one for any firm with a rating of 4 as of December 2011 and zero otherwise. $Post$ is a post-treatment indicator equal to 1 in each month after February 2012. X_{iy-1} is a vector of firm characteristics (size, tangibility, and profitability). $NBank = ln(1 + Number\ of\ banks)$. Robust standard errors are clustered by firm, and are reported in brackets; *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 3
Effect of the ACC policy on Leverage of Debt Users

	Single-bank						All firms		Multibank
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Firm,Time	BankxTime	IndxQuarter	Covariates	-	-	-	-	g(main)
ACC×post	0.0203***	0.0182***	0.0167***	0.0147***	0.0139***	0.0140***	0.0074***	0.0203***	0.0076***
	(0.0029)	(0.0029)	(0.0029)	(0.0029)	(0.0030)	(0.0030)	(0.0025)	(0.0060)	(0.0020)
Size (lag)				0.5114***	0.5822***	0.5854***	0.5509***	0.5592***	0.2556***
				(0.0850)	(0.0899)	(0.0898)	(0.0469)	(0.0468)	(0.0428)
Tangibility (lag)					0.0008	0.0008	0.0039	0.0038	0.0159***
					(0.0008)	(0.0008)	(0.0025)	(0.0025)	(0.0033)
Profitability (lag)						-0.0002***	-0.0000	-0.0000	0.0001**
						(0.0001)	(0.0001)	(0.0001)	(0.0001)
ACC×post×SingleBank							0.0084**		
							(0.0040)		
post×SingleBank							-0.0257***		
							(0.0032)		
ACC×post×N Bank								-0.0090	
								(0.0055)	
post×N Bank								0.0300***	
								(0.0043)	
Bank-Time FE		yes	yes	yes	yes	yes	yes	yes	yes
Industry-Qtr FE			yes	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
N of clusters (firms)	2487	2483	2483	2429	2202	2202	6358	6358	4152
Observations	54,668	54,580	54,578	53,007	47,783	47,783	138,636	138,636	90,763
R^2	0.92	0.93	0.93	0.93	0.91	0.91	0.86	0.86	0.81

Note: This table presents DID estimates of the effect of the ACC reform (February 2012) on the leverage of existing borrowers, with at least 5% leverage in 2011. We follow a DID strategy and estimate the following equation: $L_{it} = \alpha_i + \beta \mathbb{1}_{ACC_i} \times Post_t + Bank_{kt} + Ind_{jT} + \Gamma' X_{iy-1} + \epsilon_{it}$, where i indexes firm, j indexes industry, k indexes bank (or main lender for multi-bank firms), t denotes time in months and T denotes quarters. The dependent variable is leverage (L_{it}) defined as $L_{it} = Debt_{it}/TA_{i2011}$, where TA_{i2011} is the firm's total asset value in 2011. α_i is a firm fixed effect; $Bank_{kt}$ is a (main) bank–month fixed effect; Ind_{jT} is an industry-quarter fixed effect. The sample consists of all 4-rated firms (newly eligible borrowers or "ACC firms", i.e., treated firms) and 5+ rated firms (closest ineligible borrowers on the internal Credit Risk Rating scale of the Banque de France) as rated in December 2011 that meet the data requirements detailed in the text, and have at least 5% leverage in 2011. The $\mathbb{1}_{ACC_i}$ indicator takes a value of one for any firm with a rating of 4 as of December 2011 and zero otherwise. $Post$ is a post-treatment indicator equal to 1 in each month after February 2012. X_{iy-1} is a vector of firm characteristics (size, tangibility, and profitability). $NBank = ln(1 + Number\ of\ banks)$. Robust standard errors are clustered by firm, and are reported in brackets; *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 4
Effect of the ACC policy conditional on measures of Bank Relationship Depth

	Single-bank Firms		
	(1)	(2)	(3)
Condition for which $D = 1$	$RL \geq 6y$ (p50)	$LargeScope = 1$	$RL \geq 6y \cap LargeScope$
ACC×post×D	0.0739**	0.0270	0.1116*
	(0.0339)	(0.0507)	(0.0609)
ACC×post	0.0240	0.0629***	0.0524***
	(0.0233)	(0.0183)	(0.0181)
post×D	-0.0012	0.0424	0.0018
	(0.0235)	(0.0362)	(0.0412)
Covariates	yes	yes	yes
Bank-Time FE	yes	yes	yes
Industry-Qtr FE	yes	yes	yes
Firm FE	yes	yes	yes
N of clusters (firms)	2,967	2,967	2,967
Observations	63,957	63,957	63,957
R^2	0.44	0.44	0.44

Note: *LargeScope* is an indicator set to one if firm i has a lending relationship with its bank that is not limited to a pure credit exposure and includes a range of different other products (e.g., factoring, leasing, and so forth). Covariates are a vector of firm characteristics (size, tangibility, and profitability). Robust standard errors are clustered by firm, and are reported in brackets; *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 5
Effect of the ACC policy conditionnal on Debt Maturity

	All Single-bank		**LR <p50**		**LR >= p50**	
	(1)	(2)	(3)	(4)	(5)	(6)
	g(ST)	g(MLT)	g(ST)	g(MLT)	g(ST)	g(MLT)
ACC×post	0.1614	0.0684***	0.4126***	0.0418	-0.0484	0.0959***
	(0.1047)	(0.0220)	(0.1547)	(0.0262)	(0.1476)	(0.0354)
Covariates	yes	yes	yes	yes	yes	yes
Bank-Time FE	yes	yes	yes	yes	yes	yes
Industry-Qtr FE	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes
N of clusters (firms)	1524	2414	666	1200	853	1209
Observations	23,307	50,676	9,951	25,138	13,269	25,426
R^2	0.49	0.59	0.53	0.61	0.47	0.58

Note: For firms with positive long term (LT) and short term (ST) debt, averaged over 2011 (i.e. $LTDebt_{2011} > 0$ and $STDebt_{2011} > 0$). LT is long-term debt with initial maturity at emission over one year; ST Debt is debt with initial maturity below one year. ST ratio is $g(STDebt/TotalDebt)$. LR is the length of the lending relationship between a single-bank firm and its lender, or between a multi-bank firm and its main lender. Covariates are a vector of firm characteristics (size, tangibility, and profitability). Robust standard errors are clustered by firm, and are reported in brackets; *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 6

Effect of the ACC policy conditional on Hard Information

	High Leverage		**Low Tangibles**		**Trade Credit User**		**Young**		**Small**	
	(1) g(Debt)	(2) g(MLT)	(3) g(Debt)	(4) g(MLT)	(5) g(Debt)	(6) g(MLT)	(7) g(Debt)	(8) g(MLT)	(9) g(Debt)	(10) g(MLT)
ACC×post×D	-0.0839**	-0.0701	-0.0903***	-0.1293***	-0.0665*	-0.1068**	-0.0931**	-0.0685	-0.0426	-0.0899**
	(0.0411)	(0.0489)	(0.0307)	(0.0327)	(0.0397)	(0.0475)	(0.0390)	(0.0427)	(0.0341)	(0.0388)
ACC×post	0.0971**	0.0877*	0.0991***	0.1009***	0.1219***	0.1313***	0.0905***	0.0802***	0.1001***	0.0990***
	(0.0386)	(0.0461)	(0.0226)	(0.0268)	(0.0332)	(0.0408)	(0.0221)	(0.0256)	(0.0227)	(0.0264)
post×D	-0.1447***	-0.1021**	-0.0259	0.0370	-0.0211	0.0024	-0.0357	-0.0058	-0.0072	0.0489*
	(0.0335)	(0.0402)	(0.0252)	(0.0285)	(0.0323)	(0.0403)	(0.0232)	(0.0232)	(0.0227)	(0.0277)
Covariates	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Bank-Time FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry-Qtr FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
N of clusters (firms)	2671	2691	2968	2691	2783	2536	2671	2691	2968	2691
Observations	55,997	57,306	63,041	57,306	59,142	54,028	55,997	57,306	63,041	57,306
R^2	0.44	0.58	0.42	0.58	0.42	0.58	0.43	0.58	0.42	0.58

Note: $HighLeverage$ is an indicator equal to 1 for firm with average leverage in 2011 above the sample median. $LowTangibles$ is an indicator equal to 1 for firm with ratio of tangible assets to total assets in 2011 in the bottom quintile of the distribution. $TradeCreditUsers$ is an indicator equal to 1 for firms which are net credit users i.e. (Payables - receivables) > 0. $Young$ is an indicator equal to 1 if firm age is no greater than 5 years in 2011. $Small$ is an indicator equal to 1 for firms with less than 10 employees in 2011. Covariates are a vector of firm characteristics (size, tangibility, and profitability). Robust standard errors are clustered by firm, and are reported in brackets; *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 7

Effect of the ACC policy conditional on Hard Information

Subsample: Single-bank firms with Lending Relationship length≥median

	High Leverage		**Low Tangibles**		**Trade Credit User**		**Small**	
	(1) g(Debt)	(2) g(MLT)	(3) g(Debt)	(4) g(MLT)	(5) g(Debt)	(6) g(MLT)	(7) g(Debt)	(8) g(MLT)
ACC×post×D	-0.1440***	-0.1421**	-0.1162**	-0.1552***	-0.0985*	-0.1267*	-0.1267**	-0.1664**
	(0.0520)	(0.0665)	(0.0466)	(0.0531)	(0.0537)	(0.0682)	(0.0545)	(0.0685)
ACC×post	0.1502***	0.1400**	0.1254***	0.1151***	0.1694***	0.1569***	0.1429***	0.1301***
	(0.0459)	(0.0585)	(0.0296)	(0.0372)	(0.0431)	(0.0567)	(0.0311)	(0.0383)
post×D	-0.1202***	-0.0774	-0.0454	0.0332	-0.0123	-0.0200	0.0251	0.0593
	(0.0402)	(0.0528)	(0.0409)	(0.0493)	(0.0425)	(0.0582)	(0.0415)	(0.0583)
Covariates	yes	yes	yes	yes	yes	yes	yes	yes
Bank-Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Industry-Qtr FE	yes	yes	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes
N of clusters (firms)	1515	1344	1577	1396	1519	1357	1577	1396
Observations	31,711	28,280	33,174	29,478	32,009	28,702	33,174	29,478
R^2	0.43	0.59	0.42	0.57	0.43	0.58	0.42	0.57

Note: $HighLeverage$ is an indicator equal to one for firms with average leverage levels in 2011 above the sample median. $LowTangibles$ is an indicator equal to 1 for firm with ratio of tangible assets to total assets in 2011 in the bottom quintile of the distribution. $TradeCreditUsers$ is a indicator equal to 1 for firms with 2011 ratio of (Receivables-Payables) over Total Assets below the sample median. $Small$ is a indicator equal to 1 for firms with less than 10 employees in 2011. Covariates are a vector of firm characteristics (size, tangibility, and profitability). Robust standard errors are clustered by firm, and are reported in brackets; *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 8
Effect of the ACC policy on High Growth ("Gazelle") and Young Firms

	Single-bank firms			Multibank firms		
	(1) G=1 if Gazelles	(2) G=1 if High Sales	(3) G=1 if Age<=5y (p10)	(4) G=1 if Gazelles	(5) G=1 if High Sales	(6) G=1 if Age<=5y (p10)
ACC×post×G	0.1182	0.1159*	0.0978	0.1614**	0.1195**	0.1614**
	(0.2358)	(0.0692)	(0.2430)	(0.0753)	(0.0549)	(0.0753)
ACC×post	0.0805***	0.0811***	0.0893***	0.0188	0.0135	0.0188
	(0.0196)	(0.0221)	(0.0210)	(0.0149)	(0.0152)	(0.0149)
post×G	0.0681	-0.0792*	0.0697	-0.0181	-0.0891**	-0.0181
	(0.2184)	(0.0477)	(0.2237)	(0.0492)	(0.0430)	(0.0492)
Covariates	yes	yes	yes	yes	yes	yes
Bank-Time FE	yes	yes	yes	yes	yes	yes
Industry-Qtr FE	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes
N of clusters (firms)	2295	2294	2294	4327	4327	4327
Observations	52,889	48,477	48,477	101,139	101,139	101,139
R^2	0.43	0.42	0.42	0.40	0.40	0.40

Note: High growth ("gazelle") firms are identified from their sales growth rates in each of the years 2009, 2010 and 2011. *Gazelle* is an indicator equal to one when firm sales growth is 10% or greater in each of these three consecutive years. *HighSales* is an indicator equal to one if the sales to total assets ratio is in the two highest deciles in 2011. Covariates are a vector of firm characteristics (size, tangibility, and profitability). Robust standard errors are clustered by firm, and are reported in brackets; *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 9

Effect of the ACC policy on the probability of Credit Rating Downgrades

	D=1 if(Downgrade >= 2 notches below Dec11 rating)					
	(1) Singlebank	(2) Multibank	(3) Singlebank	(4) Singlebank	(5) Multibank	(6) Multibank
ACC×postJune	-0.0026**	0.0025*				
	(0.0012)	(0.0014)				
ACC×2012q2			0.0018		0.0028	
			(0.0015)		(0.0019)	
ACC×2012q3			0.0004	-0.0006	0.0047**	0.0033*
			(0.0018)	(0.0018)	(0.0022)	(0.0019)
ACC×2012q4			-0.0028	-0.0037**	0.0034*	0.0021
			(0.0019)	(0.0019)	(0.0020)	(0.0018)
ACC×2013q1			-0.0023	-0.0041**	0.0034	0.0020
			(0.0019)	(0.0020)	(0.0024)	(0.0021)
Covariates	yes	yes	yes	yes	yes	yes
Bank-Time FE	yes	yes	yes	yes	yes	yes
Industry-Qtr FE	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes
N of clusters (firms)	2743	4773	3045	2743	4773	4773
Observations	38,353	66,777	42,575	38,353	66,777	66,777
R^2	0.09	0.10	0.09	0.09	0.10	0.10

Note: In columns1 to 4, the dependent variable is an indicator equal to one in the month the firm's credit rating is downgraded from its December 2011 rating, if this occurs, and zero otherwise. In columns 5 to 8, the dependent variable is similar, but equals one only if the firm is downgraded 2 or more notches. The sample period for columns 5 to 8 begins with January 2012. Covariates are a vector of firm characteristics (size, tangibility, and profitability). Robust standard errors are clustered by firm, and are reported in brackets; *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 10

Effect of the ACC policy on Defaults on Debt to Suppliers

	2011m3–2013m2				2011m3–2013m12	
	(1) Plain	(2) Controls	(3) Dynamic	(4) Pretrend	(5) Controls	(6) Dynamic
ACC×post	-0.0101*	-0.0127**			-0.0149**	
	(0.0057)	(0.0064)			(0.0060)	
ACC×pre			0.000918			0.000576
			(0.0047)			(0.0047)
ACC×$1_{t>2012m2\,\&\,t\leq 2012m8}$			-0.00392			-0.00428
			(0.0065)			(0.0066)
ACC×$1_{t>2012m8\,\&\,t\leq 2013m2}$			-0.0205*			-0.0207*
			(0.0114)			(0.0114)
ACC×$1_{t>2013m2}$						-0.0184**
						(0.0079)
ACC specific trend				-0.0000406		
				(0.0006)		
Covariates		yes	yes	yes	yes	yes
Bank FE	yes	yes	yes	yes	yes	yes
Industry-time FE	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes
Num. clustering firms	3,045	2,743	2,743	2,743	2,743	2,743
Observations	73,025	65,127	65,127	32,260	83,838	83,838
R^2	0.13	0.11	0.11	0.14	0.12	0.12

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The dependent variable, default, is the total monthly amount of payment default on commercial bills (debts to suppliers) times twelve (i.e. annualized) divided by the lagged value of total (annual) accounts payable. Covariates are one-year lagged value of firm's size (natural log of total assets), tangibility (tangible assets over total assets), and profitability (ebitda over total assets). *Pre* dummy is equal to one from September 2011 to February 2012. Standard errors are clustered by firm. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 11

Test for Crowding Out effects on 5+ single-bank borrowers

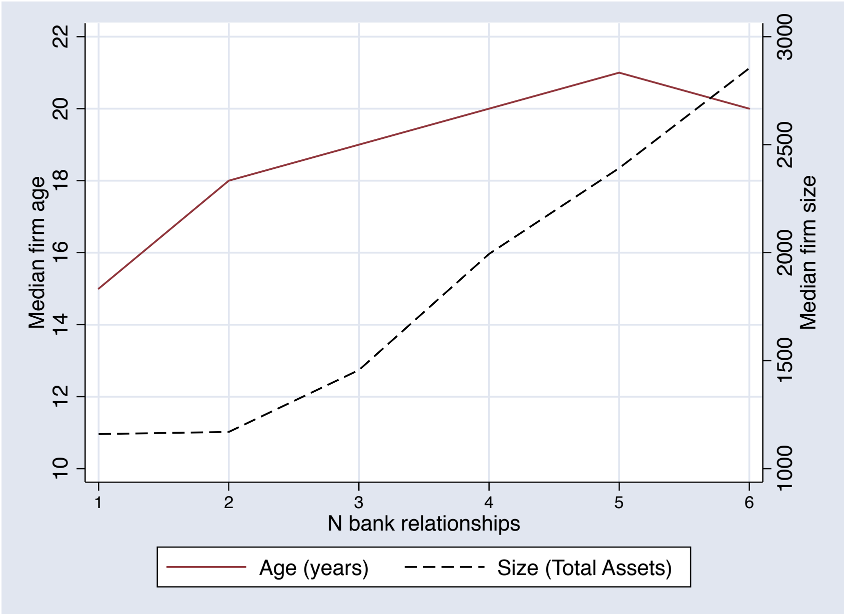
	(1)	(2)	(3)	(4)	(5)	(6)
	Firm,Time	BankxTime	IndxQter	Covariates	-	-
$5+ \times$post	-0.0228	-0.0160	-0.0124	-0.0124	-0.0173	-0.0183
	(0.0225)	(0.0229)	(0.0238)	(0.0238)	(0.0268)	(0.0270)
Size (lag)			1.6768***	1.6768***	1.8405***	1.8574***
			(0.4837)	(0.4837)	(0.5981)	(0.5978)
Tangibility (lag)					0.0880**	0.0903**
					(0.0350)	(0.0352)
Profitability (lag)						0.0012
						(0.0014)
Bank-Time FE		yes	yes	yes	yes	yes
Industry-Qtr FE						yes
Firm FE	yes	yes	yes	yes	yes	yes
N of clusters (firms)	1562	1561	1509	1509	1304	1302
Observations	33,594	33,572	32,116	32,116	27,462	27,418
R^2	0.41	0.42	0.43	0.43	0.43	0.43

Note: The sample is limited to single-bank firms rated 5+ and 5 (one notch lower), all of which are ineligible for the ACC policy. We estimate the following equation: $L_{it} = \alpha_i + \beta \mathbb{1}_{5+_i} \times Post_t + Bank_{kt} + Ind_{jT} + \Gamma' X_{iy-1} + \epsilon_{it}$, where i indexes firm, j indexes industry, k indexes bank (or main lender for multi-bank firms), t denotes time in months and T denotes quarters. The dependent variable is the cumulative growth rate in the outstanding amount of drawn credit, $g(Debt_{it})$ defined as $g_{it} = (D_{ikt} - \overline{D}_{i2011})/\overline{D}_{i2011}$, where $\overline{D}_{i2011}$ is the firm's average debt in 2011. α_i is a firm fixed effect; $Bank_{kt}$ is a (main) bank–month fixed effect; Ind_{jT} is an industry-quarter fixed effect. The $\mathbb{1}_{5+_i}$ indicator takes a value of one for any firm with a rating of 5+ as of December 2011 and zero otherwise. $Post$ is equal to 1 in each month after February 2012. X_{iy-1} is a vector of firm characteristics (size, tangibility, and profitability). Robust standard errors are clustered by firm, and are reported in brackets; *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

B Main Figures

Figure 1

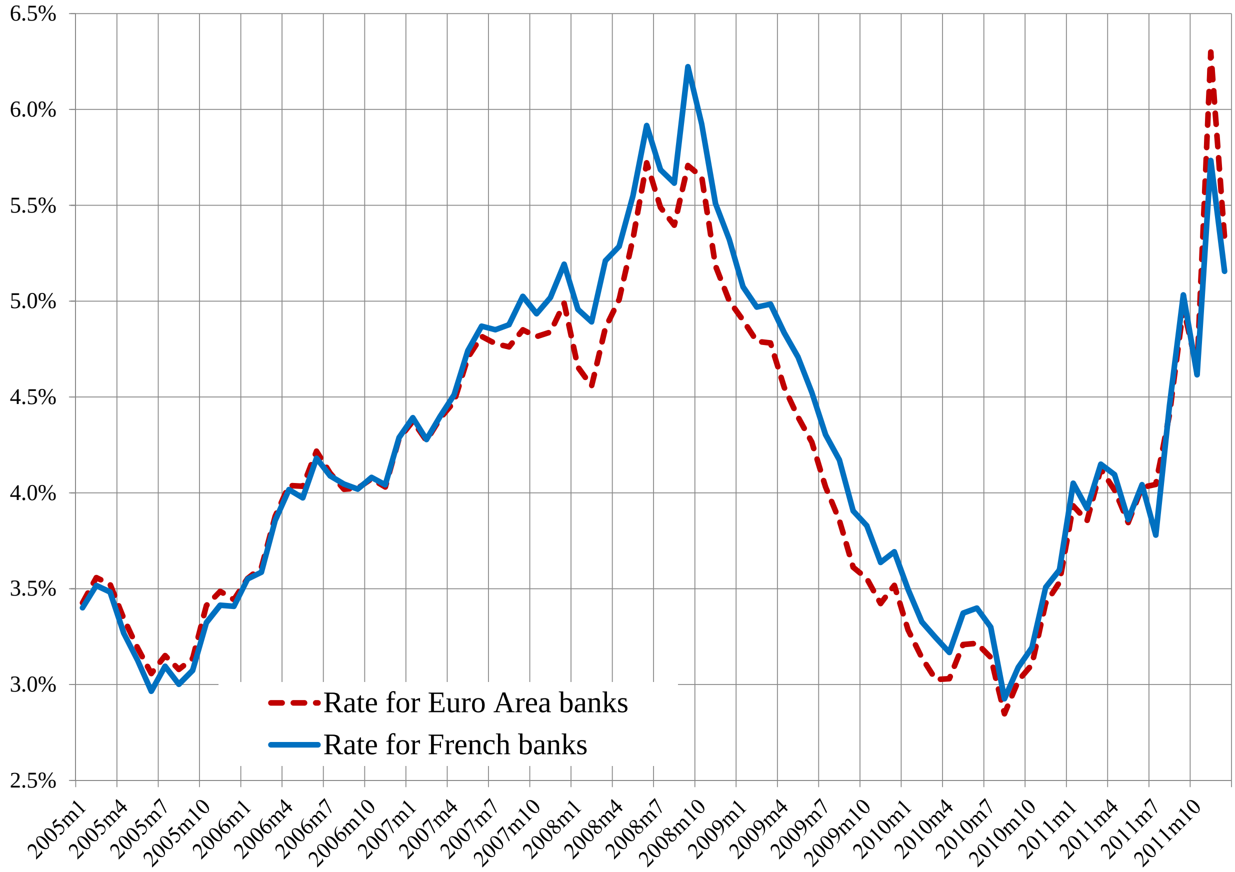
Median Firm Age and Median Firm Size by Number of Lending Relationships



Note: This figure shows the median age and size (total assets) of firms based on their number of lending relationships. The number of bank relationships is measured as follows: N-bank firms have >N-1, and ≤N lending relationships, on average, in 2011.

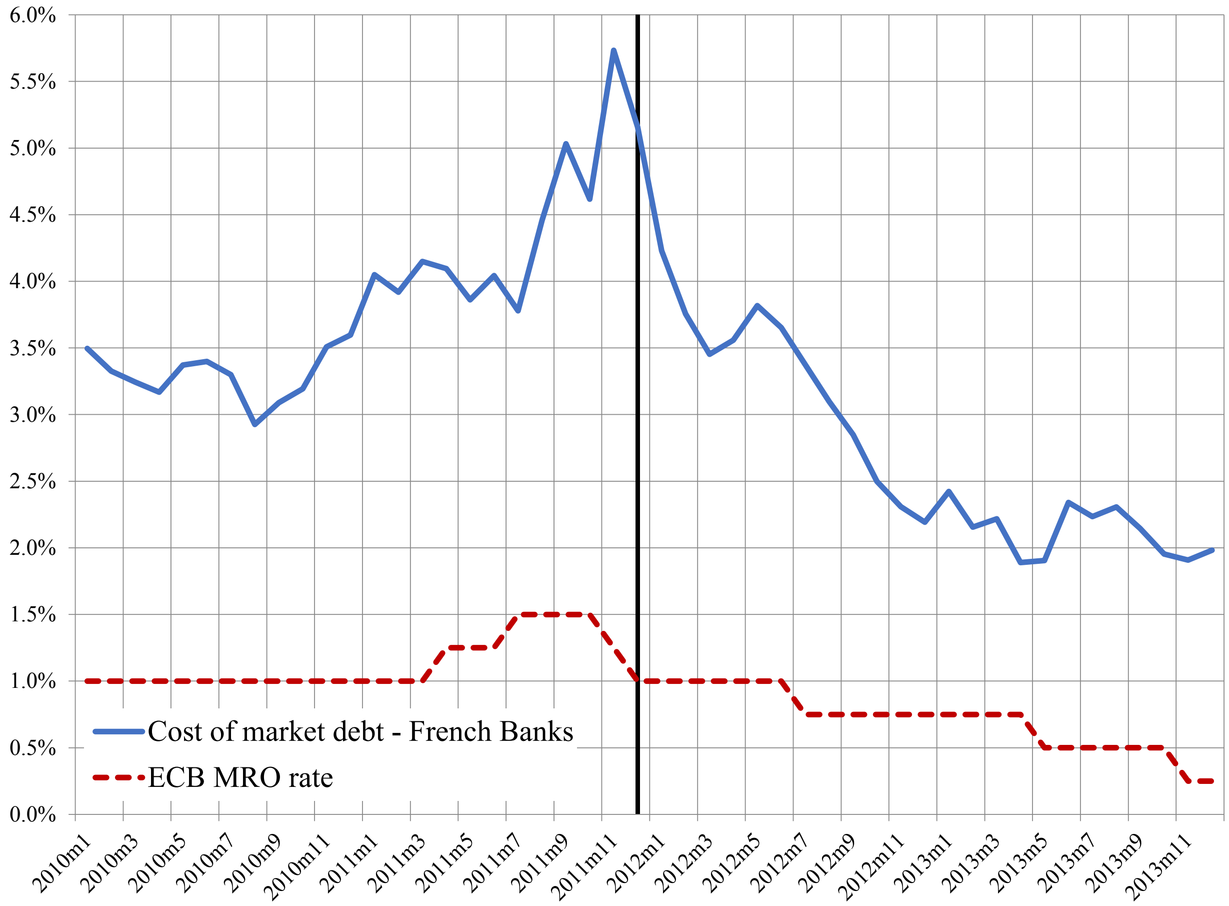
Figure 2

Bank Market Funding Cost



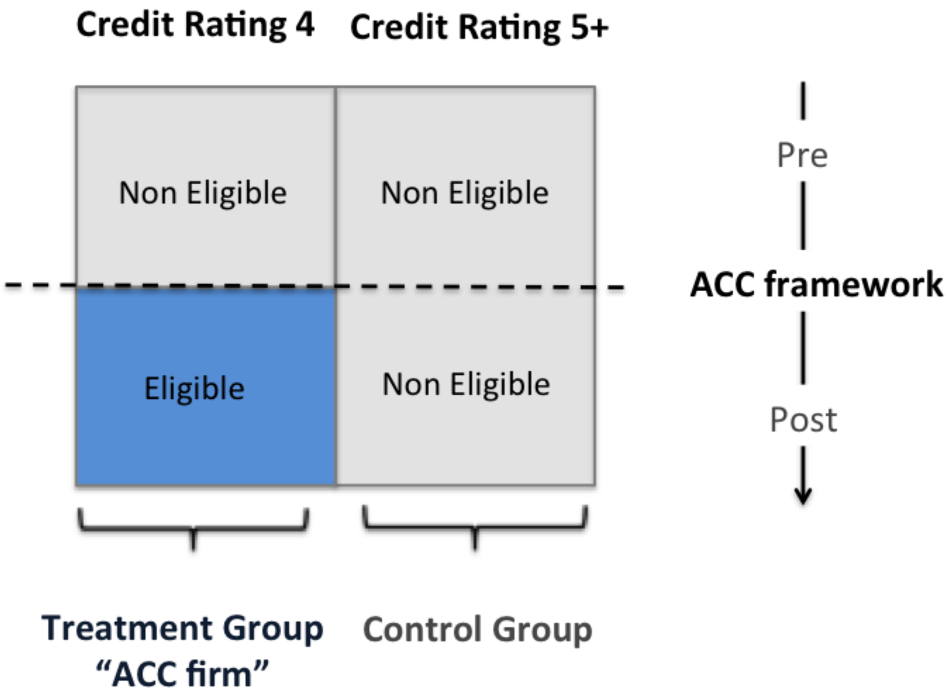
Note: This figure compares the market funding costs for both French and Euro area banks extracted from bond issues from Gilchrist and Mojon (2017) over the 2005-2011 period. The cost of bond issues is an (imperfect) proxy for banks' marginal longer-term funding cost. In the pre-period for our difference-in-differences estimate (2011, the final year in the graph) bank marginal funding costs were approximately as high as they were at the peak of the US financial crisis, suggesting substantial funding pressure.

Figure 3
Market versus ECB Funding Cost



Note: This figure compares the market funding costs for French banks extracted from bond issues from Gilchrist and Mojon (2017), with the ECB's rate for the main refinancing operations.

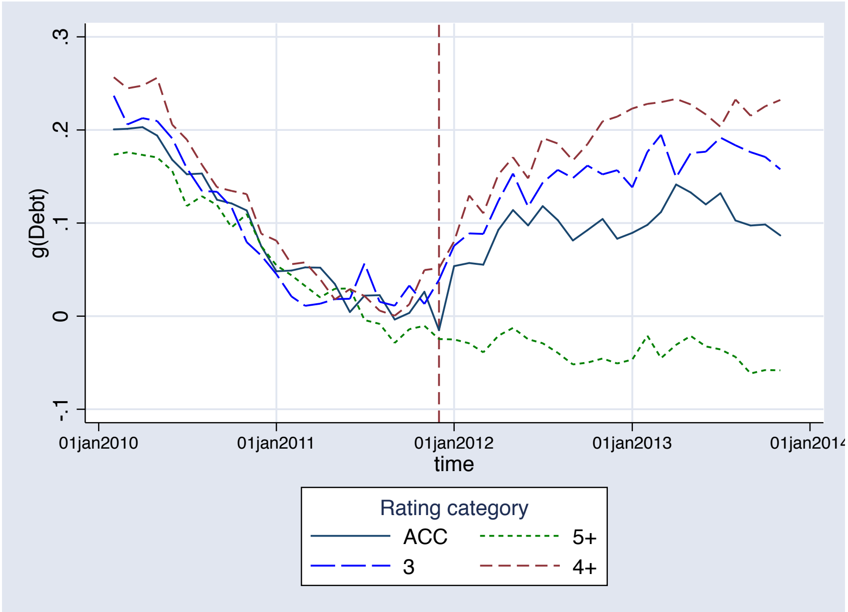
Figure 4
Empirical Design



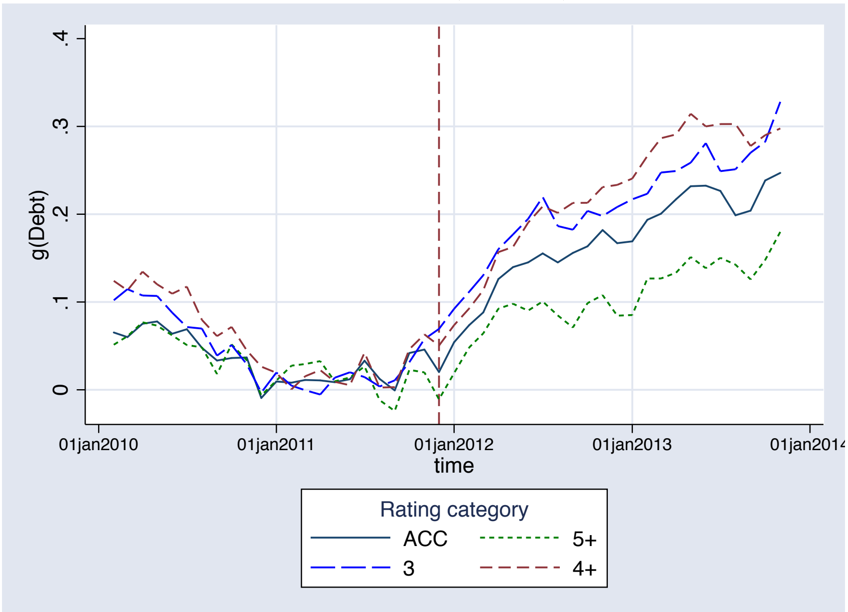
Note: This figure illustrates the empirical design for our difference in difference design (intention-to-treat). Assignment to treatment and control group is based on firms' credit rating in December 2011 - the month in which the ECB announced that national Central Banks could implement an Additional Credit Claim (ACC) policy (without specifying implementation details), and before it was known whether the Banque de France would choose to do so.

Figure 5
Trends in Credit Growth for newly eligible firms (ACC), already eligible firms (4+ and 3) and ineligible firms (5+)

Single-bank firms : ACC (rating 4), 5+, 4+, 3



Multi-bank firms : ACC (rating 4), 5+, 4+, 3



Note: The figure shows the average growth rate in debt around the ACC reform (general announcement date: December 2011 - vertical line) for newly eligible firms (ACC firms), already eligible firms (4+ rated firms and 3 rated firms which are, respectively, one notch and two notches higher on the Credit Rating scale of the Banque de France) and ineligible firms (5+ rated firms - one notch lower). Firms are assigned to credit rating categories based on their credit rating in December 2011. For each point in time, we plot the unconditional average (across firms) of the growth rate of debt relative to the firm's 2011 average: i.e. $g_{it} = (D_{it} - \overline{D}_{i2011})/\overline{D}_{i2011}$ averaged across firms. The top panel is for single-bank borrowers and the bottom panel for multi-bank borrowers. Single-bank firms have only one lending relationship on average in 2011; multi-bank firms have more than one.

Figure 6

Trends in Credit Growth for Treated and Control firms

Note: The figure shows the average growth rate in debt around the ACC reform (general announcement date: December 2011 - vertical line) for the treatment group and the control group. Note that we are not splitting the sample into single-bank and multi-bank subsamples in this graph. Assignment to treatment and control groups is based on firms' credit rating in December 2011. The treated group is composed of 4-rated firms (newly eligible borrowers or "ACC firms"). The control group is composed of 5+ rated firms (closest ineligible borrowers on the Credit Rating scale of the Banque de France). For each point in time, we plot the unconditional average (across firms) of the growth rate of debt relative to the firm's 2011 average: i.e. $g_{it} = (D_{it} - \overline{D}_{i2011})/\overline{D}_{i2011}$ averaged across firms.

Figure 7

Trends in Credit Growth for Treated and Control firms

Single-bank firms

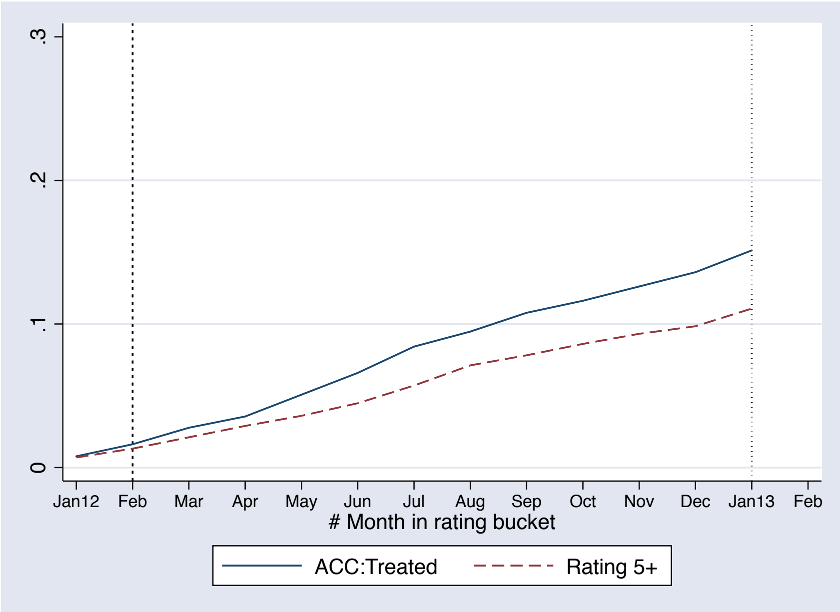
Multi-bank firms

Note: The figures show the average growth rate in debt around the ACC reform (general announcement date: December 2011 - vertical line) for the treatment group and the control group. The top panel is for single-bank borrowers and the bottom panel for multi-bank borrowers. Single-bank firms have only one lending relationship on average in 2011; multi-bank firms have more than one. Assignment to treatment and control groups is based on firms' credit rating in December 2011. The treated group is composed of 4-rated firms (newly eligible borrowers or "ACC firms"). The control group is composed of 5+ rated firms (closest ineligible borrowers on the Credit Rating scale of the Banque de France). For each point in time, we plot the unconditional average across firms, of the growth rate of debt relative to the firm's 2011 average: i.e. $g_{it} = (D_{it} - \overline{D}_{i2011})/\overline{D}_{i2011}$ averaged across firms.

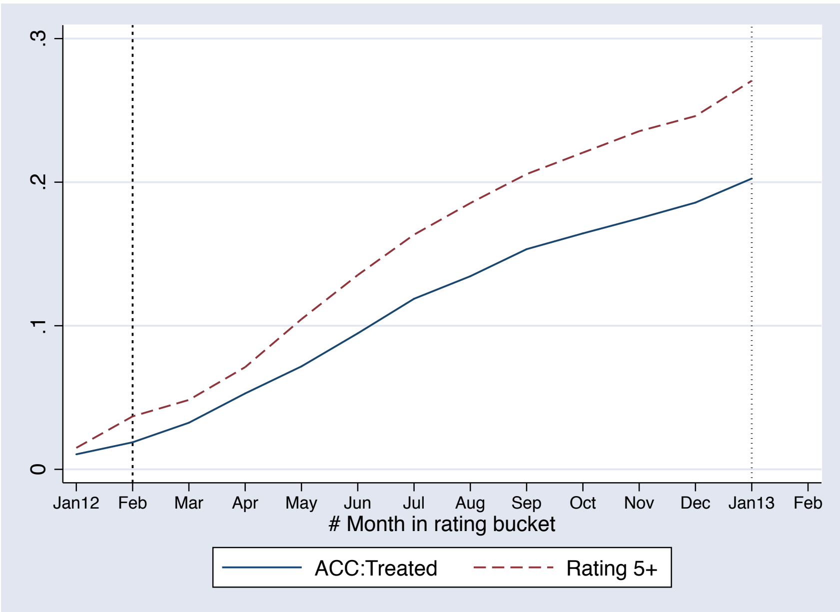
Figure 8

Cumulative Probability of Change in Credit Rating occurring next month – Single-bank firms

Rating Downgrades



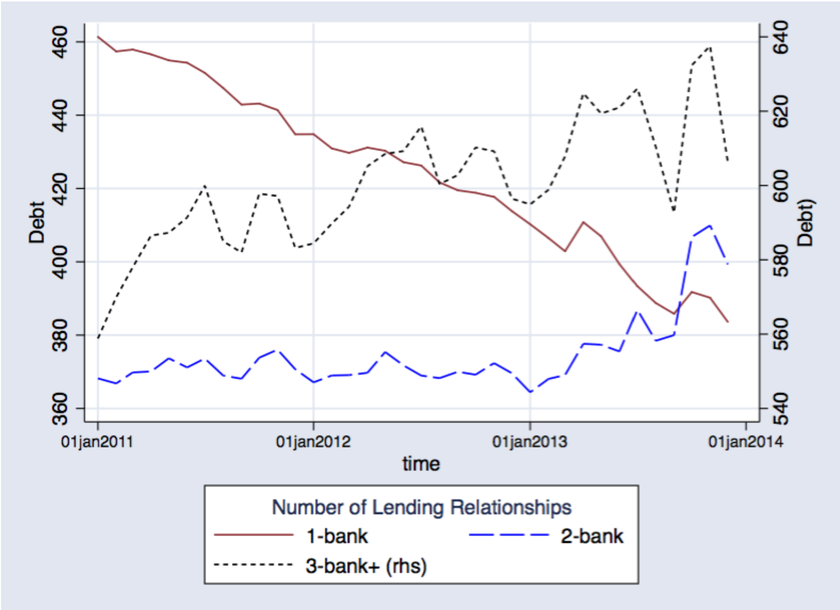
Rating Upgrades



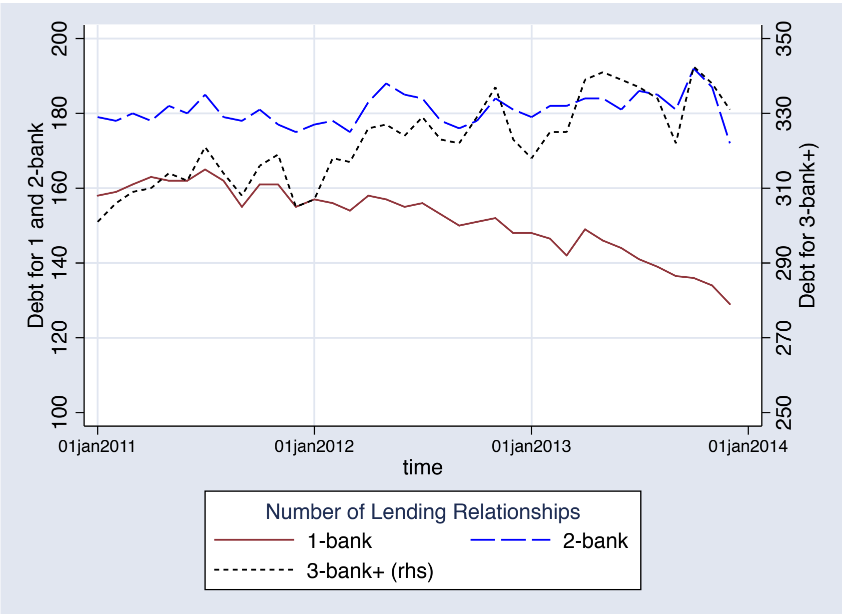
Note: The top panel of this figure shows the percentage of firms that experienced at least one downgrade of their credit rating in 2012 for treated and control firms. Assignment to treatment and control groups is based on firm credit rating in December 2011. The treated group is made of 4-rated firms (newly eligible borrowers or ACC firms). The control group is made of 5+ rated firms (closest non eligible borrowers on the internal Credit Risk Rating scale of the Banque de France). The bottom panel shows the percentage of firms that experienced at least one credit upgrade of their credit rating in 2012 for treated and control firms. After the first occurrence of a change in rating (downgrade for top panel and upgrade for bottom panel) the firm is removed from the sample. The ACC reform was adopted in February 2012.

Figure 9

Average Bank Debt by Number of Lending Relationships



Median Bank Debt by Number of Lending Relationships

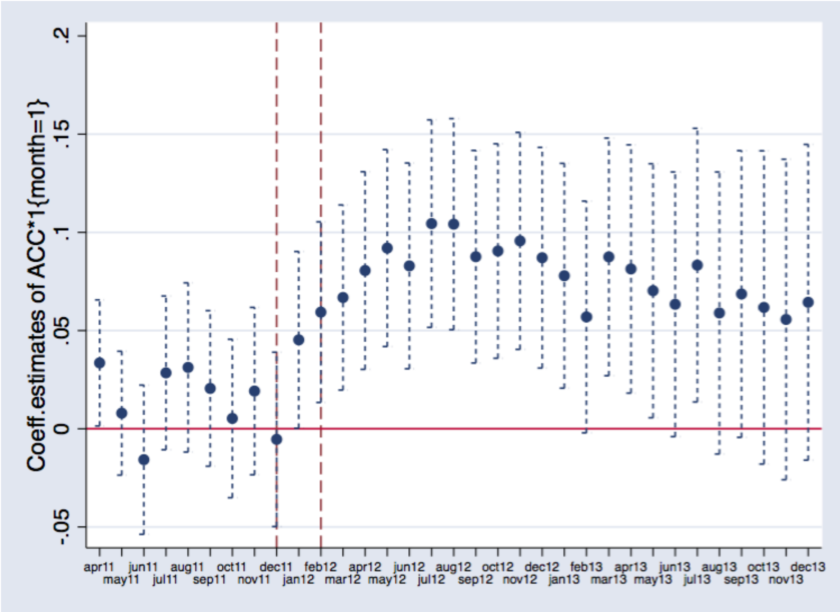


Note: These figures show the average and median outstanding amount of drawn debt for subsamples of firms based on their number of lending relationships. For each point in time, we plot the unconditional average (resp. median) of the outstanding amount of drawn credit D_{it} reported in the Credit Register. Single-bank firms have one lending relationship on average in 2011. 2-bank (respectively, 3-bank) firms have more than one and less than two (resp., three) lending relationships on average in 2011 .

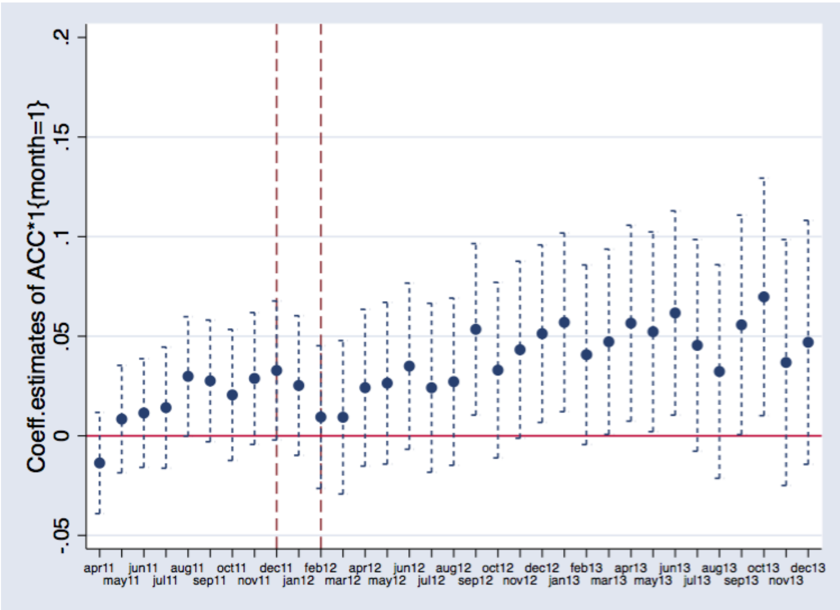
Figure 10

Monthly Dynamics of the effect of the ACC policy on Debt Growth

Single-bank firms



multi-bank firms

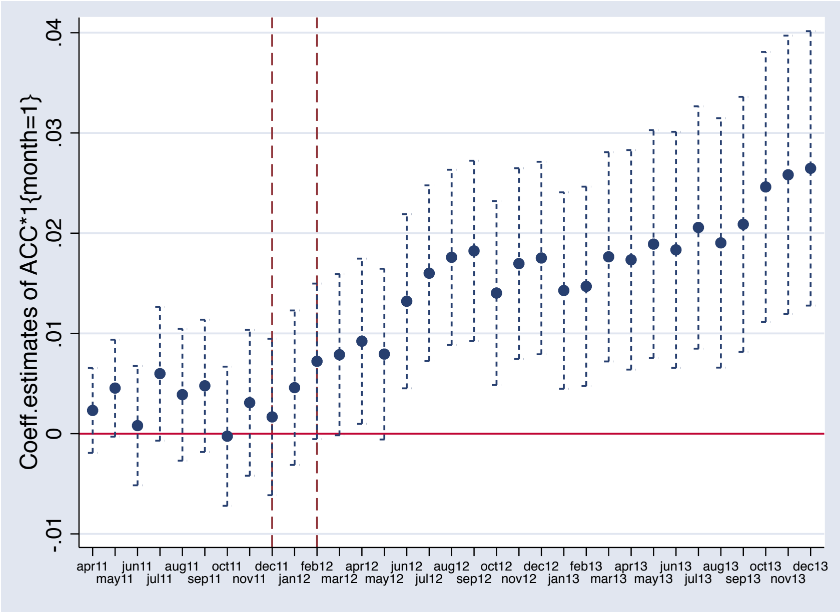


Note: The top (resp. bottom) panel of this figure shows the evolution of lending to single-bank (resp. multi-bank) firms around the ACC reform date. The specification is the same as equation (1) except that it is estimated over 2010-2013 and the $\mathbb{1}_{ACC_i} \times Post$ variable is replaced by a collection of variables $\mathbb{1}_{ACC_1} \times \sum_{t>jan2011} \mathbb{1}_t$ where $\mathbb{1}_t$ is a monthly indicator . We plot the point estimates from February 2011 (12 months prior the ACC reform) to December 2013. The dashed lines plot the 95% confidence interval and robust standard errors are clustered at the firm level .

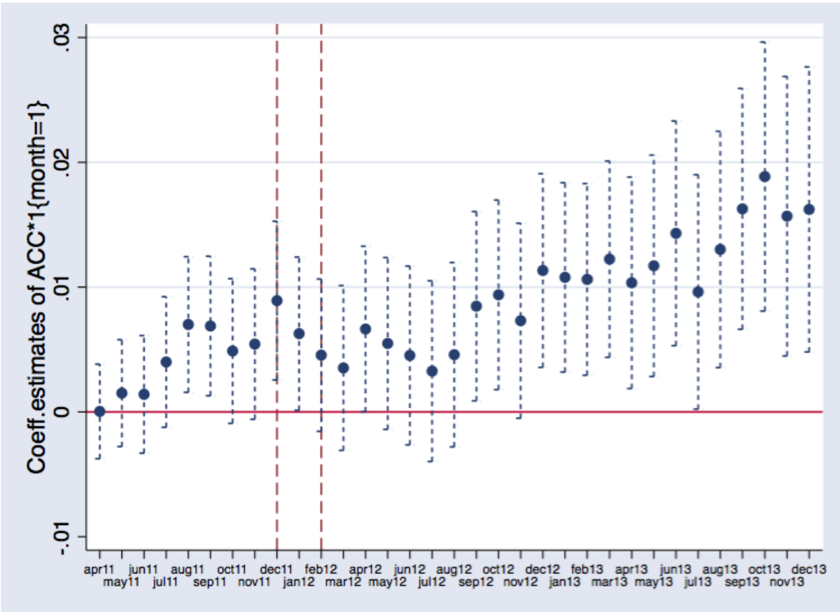
Figure 11

Monthly Dynamics of the effect of the ACC policy on Leverage

Single-bank firms



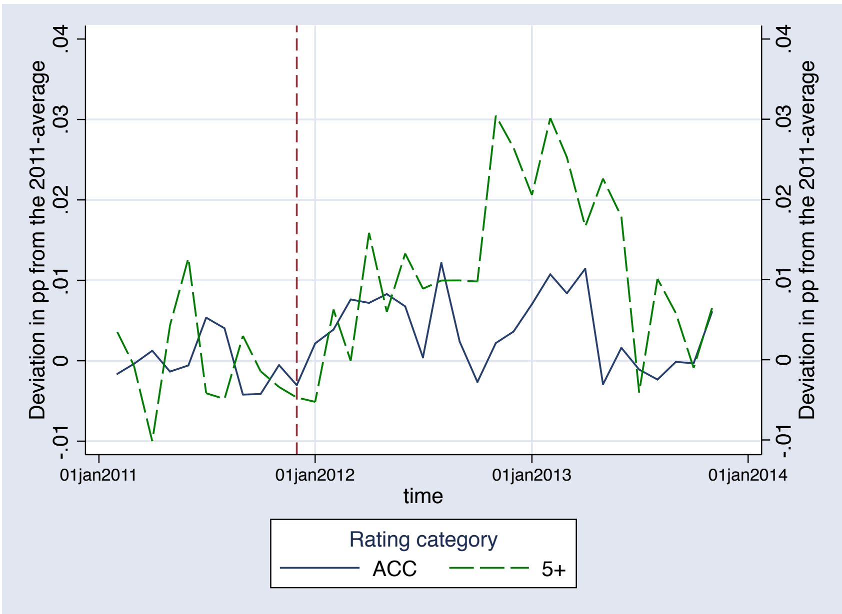
multi-bank firms



Note: The top (resp. bottom) panel of this figure shows the evolution of lending to single-bank (resp. multi-bank) firms around the ACC reform date. The dependent variable is Leverage $L_{it} = Debt_{it}/TA_{i2011}$. The sample is reduced to debt users i.e. firms whose average Leverage in 2011 is at least 5%. The specification is the same as equation (1) except that it is estimated over 2010-2013 and the $\mathbb{1}_{ACC_i} \times Post$ variable is replaced by a collection of variables $\mathbb{1}_{ACC_1} \times \sum_{t>jan2011} \mathbb{1}_t$ where 1_t is a monthly indicator . We plot the point estimates from February 2011 (12 months prior the ACC reform) to December 2013. The dashed lines plot the 95% confidence interval and robust standard errors are clustered at the firm level .

Figure 12

Defaults on Debt to Suppliers



Note: This figure depicts the evolution of defaults on debts to suppliers (commercial bills) for single-bank firms around the ACC reform date. Default is normalized (divided by) each firm's total payables, and is expressed as deviations (in percentage points) from the 2011 average.

C Additional Tables and Figures

Table 12
Composition of collateral pledged with Banque de France

Amounts after haircuts in EUR'bn	Total	Mean	Std.	P50
2011, 54 MFIs				
Marketable securities	199.4	3.70	8.7	0.2
Non marketable	63.7	1.	6.5	0.0
Credit Claims	149.7	2.8	7.5	0.0
Total	412.8	7.6	15.4	0.8
2012s1, 59 MFIs				
Marketable securities	168.8	2.9	6.3	0.3
Non marketable	13	0.2	0.6	0.0
Credit Claims	152.9	2.6	7.2	0.0
ACC	45	0.8	3.4	0.0
Total	379.7	6.4	14.3	1.0

Source: ECB, Bignon et al. (2016).
Note: MFI: Monetary and Financial Institutions.

Table 13

Parallel Trend Tests, ACC vs. Rating 5+ (one notch lower), 2011m7–2011m12.

	Single-bank			**Multibank firms**		
	(1) g(Debt)	(2) g(Debt_2010)	(3) Leverage	(4) g(Debt)	(5) g(Debt_2010)	(6) Leverage
ACC×t	-0.0059	-0.0052	-0.0003	0.0032	0.0014	0.0008
	(0.0037)	(0.0043)	(0.0006)	(0.0031)	(0.0041)	(0.0006)
Tangibility (lag)	0.0151	0.0923	0.0077	-0.0061	-0.0578	0.0051
	(0.0758)	(0.0764)	(0.0111)	(0.0464)	(0.0727)	(0.0089)
Size (lag)	-0.8809	-1.0816	-0.1066	0.0418	0.0638	0.0563
	(1.1116)	(1.0344)	(0.1238)	(0.5182)	(0.7683)	(0.0821)
Profitability (lag)	0.0001	-0.0001	0.0000	-0.0002	-0.0004	-0.0000
	(0.0006)	(0.0009)	(0.0001)	(0.0003)	(0.0005)	(0.0000)
Bank-Time FE	yes	yes	yes	yes	yes	yes
Industry-Qtr FE	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes
N of clusters (firms)	2632	2459	2201	4713	4474	4146
Observations	15,283	14,338	13,019	27,699	26,360	24,729
R^2	0.37	0.87	0.97	0.34	0.83	0.90

Note: Standard errors are clustered by firm. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively .

Table 14

Robustness Tests, ACC vs. Rating 5+ (one notch lower).

	g(Debt)		New g Definitions		
	(1)	(2)	(3)	(4)	(5)
	Clustered SE	Time Trend	g(Debt_2010)	g(Debt_2011s1)	g(Debt_2011s2)
ACC×post	0.0867***	0.0847***	0.0860***	0.1014***	0.0806***
	(0.0089)	(0.0204)	(0.0226)	(0.0202)	(0.0198)
ACC×t		0.0002			
		(0.0016)			
Covariates	yes	yes	yes	yes	yes
Bank-Time FE	yes	yes	yes	yes	yes
Industry-Qtr FE	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes
N of clusters (firms)		2671	2508	2628	2643
N of clusters (Bank-Qtr)	153				
Observations	55,997	55,997	52,641	55,549	55,790
R^2	0.43	0.43	0.75	0.54	0.42

Note: Clustered SE is a variant of the baseline specification clustering the standard errors at the Bank-Quarter level. Time Trend adds an ACC specific linear time trend to the main specification. g(Debt_2010) uses the cumulative growth rate in debt with respect to 2010 as the left hand side variable. g(Debt_2011s1) (resp. 2011s2) uses the cumulative growth rate in debt with respect to the first semester of 2011 (resp. the second semester) as the left hand side variable. Covariates are one-year lagged value of firm's size (natural log of total assets), tangibility (tangible assets over total assets), and profitability (ebitda over total assets). Standard errors are clustered by firm. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. .

Table 15
Effect of the ACC Policy on non-pledgeable types of debt.

	(1) g(Undrawn Debt)	(2) Undrawn Debt/TA_2011	(3) g(Leasing)	(4) Leasing/TA_2011
ACC×post	-0.0857	-0.0021	-0.0145	-0.0041
	(0.1094)	(0.0033)	(0.0880)	(0.0049)
Covariates	yes	yes	yes	yes
Bank-Time FE	yes	yes	yes	yes
Industry-Qtr FE	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes
N of clusters (firms)	1069	1116	607	614
Observations	15,935	24,294	11,301	13,419
R^2	0.54	0.73	0.80	0.88

Note: Covariates are one-year lagged value of firm's size (natural log of total assets), tangibility (tangible assets over total assets), and profitability (ebitda over total assets). Standard errors are clustered by firm. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table 16

Effect of the ACC Policy conditional on firm characteristics – multi-bank firms

	High Leverage		**Low Tangibles**		**Trade Credit User**		**Young**		**Small**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	g(Debt)	g(MLT)	g(Debt)	g(MLT)	g(Debt)	g(MLT)	g(Debt)	g(MLT)	g(Debt)	g(MLT)
ACC×post×D	0.0058	-0.0229	0.0117	-0.0253	0.0367	0.0699	0.0205	-0.0215	0.0310	-0.0012
	(0.0315)	(0.0445)	(0.0393)	(0.0572)	(0.0306)	(0.0429)	(0.0647)	(0.0657)	(0.0397)	(0.0595)
ACC×post	0.0058	0.0435	0.0487***	0.0696***	0.0287	0.0283	0.0305*	0.0433**	0.0430***	0.0634***
	(0.0290)	(0.0383)	(0.0163)	(0.0217)	(0.0207)	(0.0280)	(0.0157)	(0.0221)	(0.0162)	(0.0220)
post×D	-0.1779***	-0.0877**	0.0507*	0.0322	-0.0099	-0.0174	-0.0137	-0.0858**	-0.0150	-0.0209
	(0.0257)	(0.0364)	(0.0268)	(0.0423)	(0.0248)	(0.0351)	(0.0446)	(0.0428)	(0.0313)	(0.0476)
Covariates	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Bank-Time FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry-Qtr FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
N of clusters (firms)	4769	4211	5119	4524	4824	4292	4769	4211	5120	4525
Observations	101,608	87,448	109,805	94,604	103,454	89,755	101,608	87,448	109,827	94,606
R^2	0.41	0.58	0.40	0.56	0.40	0.56	0.41	0.58	0.40	0.56

Note: Leveraged: $D = 1$ if leverage higher than sample median. Low Collat.: $D = 1$ if Tangibles in the lowest 2 deciles. Youth: $D = 1$ if Age less than 6 years. Small: $D = 1$ if less than 10 employees. Covariates are one-year lagged value of firm's size (natural log of total assets), tangibility (tangible assets over total assets), and profitability (ebitda over total assets). Standard errors are clustered by firm. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table 17

Effect of the ACC Policy conditional on firms having wide bank scope – Single-bank firms

	Leveraged		Low Collat.		Small	
	(1) g(Debt)	(2) g(MLT Debt)	(3) g(Debt)	(4) g(MLT Debt)	(5) g(Debt)	(6) g(MLT Debt)
ACC×post×D	-0.1754*	-0.1398	-0.2070	-0.1065	-0.0491	-0.1985
	(0.1033)	(0.1693)	(0.1411)	(0.1870)	(0.1942)	(0.1724)
ACC×post	0.1745**	0.1676	0.1484**	0.1373	0.1652***	0.1631*
	(0.0886)	(0.1222)	(0.0615)	(0.0892)	(0.0631)	(0.0895)
post×D	-0.0850	-0.0177	-0.0752	-0.0269	-0.1524	-0.0099
	(0.0786)	(0.1213)	(0.0936)	(0.1231)	(0.1223)	(0.1393)
Covariates	yes	yes	yes	yes	yes	yes
Bank-Time FE	yes	yes	yes	yes	yes	yes
Industry-Qtr FE	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes
N of clusters (firms)	404	339	404	339	404	339
Observations	8,614	7,360	8,614	7,360	8,614	7,360
R^2	0.43	0.60	0.43	0.60	0.43	0.60

Note: Leveraged: $D = 1$ if leverage higher than sample median. Low Collat.: $D = 1$ if Tangibles in the lowest 2 deciles. Small: $D = 1$ if less than 10 employees. Covariates are one-year lagged value of firm's size (natural log of total assets), tangibility (tangible assets over total assets), and profitability (ebitda over total assets). Standard errors are clustered by firm. Standard errors are clustered by firm. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table 18
Count regressions – Monthly Number of Payment Incidents

	Single Bank		Multi Bank	
	(1)	(2)	(3)	(4)
ACC×post	-0.116	-0.160	-0.0384	-0.151*
	(-0.91)	(-1.06)	(-0.38)	(-1.81)
Size (lag)		0.424		0.288
		(0.96)		(1.28)
Tangibility (lag)		0.127		-0.00969
		(0.82)		(-0.13)
Profitability (lag)		-0.264***		-0.213***
		(-4.12)		(-5.05)
Bank FE	yes	yes	yes	yes
Industry-time FE	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes
Num. clustering firms	1,531	1,463	3,129	3,033
Observations	47,271	43,667	97,697	91,754

Note: This table shows results from a poisson model with multidimensional fixed-effect, where the dependent variable is the number of payment incident occurring in a given month. The recourse to multidimentional fixed-effects make difficult the use of negative binomial or zero-inflated models. As a consequence, overdispersion in the dependent variable's distribution is dealt through the firm-level clustering of t-statistics, provided in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively .

Table 19

New Lending Relationships

	D=1 if new LR. Mar2011-Feb2013			D=1 if N LR >N LR2011. Jan2012-Feb2013		
	(1)	(2)	(3)	(4)	(5)	(6)
	1-bank	2- and 3-bank	4-bank +	1-bank	2- and 3-bank	4-bank +
ACC×post	0.0009	-0.0064**	0.0054			
	(0.0016)	(0.0029)	(0.0061)			
ACC×postJune				0.0051	-0.0133	-0.0081
				(0.0094)	(0.0111)	(0.0227)
Covariates	yes	yes	yes	yes	yes	yes
Bank-Time FE	yes	yes	yes	yes	yes	yes
Industry-Qtr FE	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes
N of clusters (firms)	2743	3708	1114	2743	3708	1114
Observations	59,641	81,021	24,398	65,127	88,437	26,626
R^2	0.08	0.09	0.09	0.42	0.55	0.45

Note: In this table we estimate a linear probability model of having a new lending relationship. In columns 1 to 3, the dependent variable is an indicator variable equal to one in the month the firm gets a new lending relationship. In columns 4 to 6, the dependent variable is equal to 1 each month the number of lending relationships is higher than its average number of lending relationships in 2011. The sample period for columns 4 to 6 begins in January 2012. Covariates are one-year lagged value of firm's size (natural log of total assets), tangibility (tangible assets over total assets), and profitability (ebitda over total assets). Standard errors are clustered by firm. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.