Bank Lending and the European Debt Crisis: Evidence from a New Survey*

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I study the supply of credit in Italy in the years 2009–14, covering the European sovereign debt crisis period. By using a new survey, I find that 40 percent of the decline in business lending originates from the tightening of bank credit standards, with a significant change in 2011 and a seemingly greater role for supply in the South of the country. The unique regional breakdown and the wider cross-section of the new survey also improve our understanding of the variation in the data and reveal substantial differences between banks.

JEL Codes: E32, E51, G01, G21, G28, G32.

1. Introduction

The slowdown in bank lending to non-financial corporations has prompted a heated debate in several countries.[1] One side argues that the slowdown in credit originates from a reduction in supply, where banks are responsible for hurting the economy. The other side

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[1]In Italy, the 2007 growth rate of business loans was above 10 percent. Since then, such a level has never been reached again in normal times.

argues that the slowdown originates from a lack of demand. The debate grows even fiercer where policy intervention or changes to the regulations are concerned. This is because a proper course of action inevitably depends on the forces that drive the credit market. A lack of supply would require an understanding of the factors that hold back the banking industry from lending, and direct action in the sector to prevent a new credit squeeze. An example would be a request for higher capital or liquidity ratios or the setting of a gold standard for banks' business model—universal or commercial. On the other hand, a lack of demand would instead leave open the possibility for a broader set of measures, including government-backed loans to further reduce the cost of credit. In light of the growing concern about the functioning of the credit market, this paper studies the supply of credit in Italy in the years 2009–14, a period that covers the European sovereign debt crisis and that approximately coincides with the first five years of the new survey at the core of this work.[2]

It is well known that studying the supply of credit is a difficult task. A reduction in business loans, although widely debated, is uninformative about the role of supply, since the demand for credit might explain the reduction in loans. Moreover, even knowledge about banks that reduce their supply is only partially informative, since supply changes can be diverse and of unknown intensity. Laffont and Garcia (1977) and Sealey (1979) seek to overcome the problem by maintaining that some factors only drive one side of the market, Jiménez et al. (2012) by convincingly controlling for the demand of credit, and Khwaja and Mian (2008) and Paravisini (2008) by resorting to a quasi-experimental design. Nevertheless, the limitations in existing techniques have led central banks towards the use of dedicated surveys,[3] subsequently exploited in several studies.

[2]This period starts immediately after the peak of the global financial crisis and ends when the supply of credit seems to stabilize after the European sovereign debt crisis, which began at the end of 2009.

[3]The European Central Bank coordinates the Bank Lending Survey (BLS); see Berg et al. (2005). In the United States, the Federal Reserve System manages the Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS); see Schreft and Owens (1991). Similar surveys in the United Kingdom and in Japan are known as the Credit Conditions Survey (CCS) and the Senior Loan Officer Opinion Survey on Bank Lending Practices at Large Japanese Banks

Following that strand of the literature, this paper uses the new Regional Bank Lending Survey (RBLS) of the Bank of Italy to study the contribution of supply to the dynamics of lending. This is the first study to use a wide cross-section of biannual records at the bank-regional level, which are all distinctive features for this class of survey.[4] With the new data set, I provide a wide-ranging and large-scale point of view of survey data in relation to the potentially heterogeneous supply behavior of banks, identifying the factors that hold back banks from lending. This exercise cannot be done in the same way by other surveys, as they typically sample small to medium-sized groups of large banks. In fact, a cross-section of more than 400 banks permits an in-depth and broad analysis that is more complicated to perform with 11 banking groups, as in Del Giovane, Nobili, and Signoretti (2017), or with 127 monetary financial institutions from different countries, as in Altavilla et al. (2021),[5] for example. In addition, I also address the controversial issue of the interpretation and credibility of survey data on lending practices by testing different models. In fact, a perennial debate in central banks and in academics centers on whether loan officers report their view truthfully or if they have a proper understanding of the questionnaire, and the wide cross-section in this paper is a new testing environment.

In terms of methodology, this paper estimates a change in supply by combining whether a bank changes its supply and how it does so—the magnitude of the change. Finally, I describe a convenient

(SLOJ). Survey data make it easier to achieve an understanding of supply that (i) avoids strong identification assumptions (think of the assumptions in Sealey 1979); (ii) possibly includes all borrowers and relates both to common and to idiosyncratic changes (survey data do not discard firms that liaise with only one bank, as in Jiménez et al. 2012 or Amiti and Weinstein 2018, and Ciccarelli, Maddaloni, and Peydro 2015 also note that survey data apply "to the whole pool of borrowers," not only accepted borrowers); and that (iii) overcomes the gaps in non-recurring identification strategies (think of identification strategies that rely on one-off shocks, as in Khwaja and Mian 2008).

[4]In this study, not banking groups, but individual banks are broken down into different areas. The regional variation in the data will prove to be an important factor to better understand the developments of the credit market. Nobili and Orame (2015) provide a preliminary analysis that uses a different section of the RBLS.

[5]Altavilla et al. (2021) can link 116 supply-and-demand assessments to 127 monetary financial institutions (MFIs).

procedure for passing from individual to market data. The intuition recalls that of Amiti and Weinstein (2018) but applies to a different context and originates from a different setting.

Interestingly, a literal interpretation of the RBLS consistently fits the developments of the credit market, showing that supply contributed to approximately 40 percent of the decline in lending between 2009 and 2014, i.e., 1.75 out of 4.41 percentage points. I also find a substantial reduction in supply from the second semester of 2011—in conjunction with a peak of the yield differential between Italian and German 10-year government bonds, a measure of the severity of crisis. The supply of credit also seems to play a greater role in determining the dynamics of lending in the South of the country. The data also reveal substantial differences between banks, as illiquid, profitable, efficient, and group-member banks reduce their supply further. Banks in larger groups display a different supply pattern, with greater tightenings and easings. Capital and funding seem to play no significant role. An alternative estimator, which takes into account that some of the distinguishing features of a bank can be correlated, selects a low dependence on interest income and group membership as the principal factors that negatively affect the supply of credit during the crisis. To summarize, I find that banks that have a less traditional commercial business model and that are more connected to other financial players cut their supply more than other banks.

The work is related to the literature that uses survey data to test the "credit view" pioneered by Bernanke and Blinder (1988). Most of this literature uses aggregate survey data to study how credit supply affects lending and economic activity. Among others, Lown and Morgan (2006) and Demiroglu, James, and Kizilaslan (2012) find that a supply tightening is related to a slowdown in lending and economic activity.[6]

Closer to my approach, Del Giovane, Eramo, and Nobili (2011), Bassett et al. (2014), and Altavilla et al. (2021) use individual data. Bassett et al. (2014), for instance, find that credit supply accounts for 40 percent of lending variations in 1991–2012 and Del

[6]See also Lown, Morgan, and Rohatgi (2000), Cunningham (2006), Bayoumi and Melander (2008), Swiston (2008), Cappiello et al. (2010), De Bondt et al. (2010), Hempell and Kok (2010), Haltenhof, Lee, and Stebunovs (2014), Buca and Vermeulen (2015), and Ciccarelli, Maddaloni, and Peydro (2015).

Giovane, Eramo, and Nobili (2011) find that supply accounts for between –2.3 and –3.1 percentage points in each year in 2007–09. Del Giovane, Nobili, and Signoretti (2017) also show that the cumulative supply-induced reduction in the stock of loans is approximately 8 percentage points in 2007–12.[7]

The contribution to the literature is twofold. First, I test a new survey and I show that its unique regional breakdown and its wider cross-section of banks improve our understanding of the variation in the data. Second, I shed light on controversial issues still open in the literature about the interpretation and credibility of survey data.[8]

Furthermore, the work contributes to the literature that studies the possibly heterogeneous supply behavior of banks—see, among others, Kashyap and Stein (2000). The issue is still open to debate and I provide a wide-ranging point of view of survey data. Bassett et al. (2014) find that most bank-level variables have statistically significant but modest effects on lending standards and Bofondi, Carpinelli, and Sette (2018) find an aggregate reduction in supply after the first half of 2011 that is not explained by heterogeneity in bank characteristics. By contrast, I show that bank characteristics significantly affect lending.[9]

In that literature, large and well-capitalized banks tend to be less responsive to shocks, particularly monetary policy shocks. Maddaloni and Peydro (2013) find that banks entering the global financial crisis with more capital soften their lending conditions more, but Lown and Morgan (2006) find a weak to insignificant correlation between bank capital ratios and credit standards. In addition, Alessandri and Bottero (2017) and Banerjee, Sette, and Gambacorta (2017) show that well-capitalized banks reduce their supply less. In line with Lown and Morgan (2006), I find that capital plays no significant role in the supply of credit and the result holds true

[7] According to Del Giovane, Nobili, and Signoretti (2017), supply accounts for 35 percent of credit reduction in 2008–09 and 45 percent in 2011–12. I am grateful to Federico M. Signoretti for doing this calculation.

[8] I am grateful to Robert DeYoung for suggesting doing this, which allowed me to acquire a better understanding of the information content of the new data set.

[9] With a focus on unconventional monetary policy, Altavilla et al. (2021) find that banks' strength influences credit supply.

even when considering different definitions of banks' distance from regulatory insolvency.

Finally, Kashyap and Stein (2000) show that banks' liquidity affects their lending response to monetary policy shocks, Khwaja and Mian (2008) find a significant effect of liquidity shocks on credit supply, and Demirgüç-Kunt and Huizinga (2010) show that banks relying more on non-interest income and non-deposit funding increase their fragility. Beltratti and Stulz (2012) find that banks with good performances had lower returns before the global financial crisis and that banks from countries with more restrictions on bank activities reduced loans less. Furthermore, Bonaccorsi di Patti and Sette (2016) show that in 2007 and in 2008 the transmission of the securitization freeze to bank supply was weaker for banks with more liquid assets. Although the funding mix plays no significant role in my analysis, I find that liquidity positively affects lending and that higher returns and dependence on non-interest income are related to larger reductions in credit supply. Furthermore, group-members reduced their supply more than other banks.

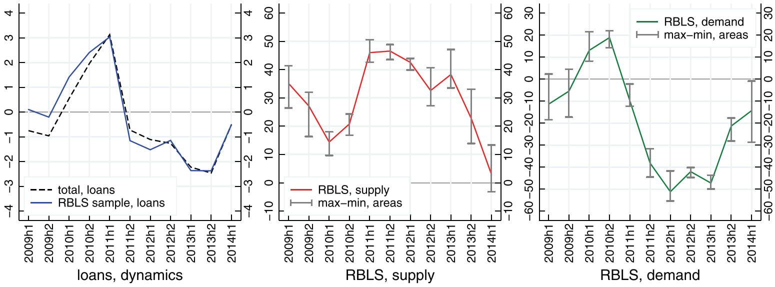
The rest of this paper is structured as follows. Section 2 introduces the data set. Section 3 develops the empirical strategy and Section 4 shows the estimates, which are then challenged in Sections 5 and 6. Section 7 aggregates the data, which are then analyzed in detail in Sections 8 and 9. Section 10 concludes.

2. Data Sources and Descriptive Analysis

In this work, I match bank-area survey data on lending practices with bank-area lending to firms. A key source of data is the RBLS, a new regional survey on bank lending carried out by the local branches of the Bank of Italy. The survey covers an unbalanced panel of 420 banks between 2009 and 2014, which is an extraordinary number of banks for this type of survey.[10] The sample accounts for

[10] Del Giovane, Eramo, and Nobili (2011) work with an unbalanced panel of 11 banking groups and Bassett et al. (2014) with 68 banks that belong to a publicly traded American bank holding company. Altavilla, Darracq Pariès, and Nicolletti (2015) work with 137 banking groups and Altavilla et al. (2021) with 116 supply-and-demand assessments that can be linked to 127 monetary financial institutions (MFIs) from different countries. None of them use data at the sub-national level.

Figure 1. Loans and Survey Indicators



Note: Loans to non-financial corporations (percentage points; half-yearly growth rates adjusted—securitizations, reclassifications, and other variations that are not a result of ordinary transactions—at the national bank level) and RBLS indicators (net percentages, percentage points) for non-financial corporations. The net percentage is the simple difference between the share of banks reporting a tightening (increase) in credit standards (demand) and the share of those reporting an easing (decrease). Positive (negative) values for the supply indicator reflect a tightening (easing) in supply, positive (negative) values for the demand indicator reflect an increase (decrease) in demand. "Max" and "Min" refer to maximum and minimum values among the net percentages of the four Italian areas. See Appendix B.

90 percent of the Italian bank-intermediated business credit market, accurately reflecting market trends (Figure 1). Almost all intermediaries rated as active banks are contacted by the closest branch of the Bank of Italy.[11] To the best of my knowledge, there is full compliance, namely 100 percent of contacted banks responded, and the only reason for the sample being unbalanced is market entry and exit. Hence, as is common for this type of survey, there is no controversy over compliance, even though truth-telling is an issue.[12]

[11] Cassa Depositi e Prestiti and Banco Posta are not in the sample because they are either linked to the Italian government or to the Italian postal service.

[12] On truth-telling, both Schreft and Owens (1991) and Del Giovane, Eramo, and Nobili (2011) are concerned by the low number of supply easings in their surveys. Schreft and Owens (1991) state that "as tightenings outnumbered easings from 1967 through 1983, if we take the survey results literally, lending standards would have been unbelievably stringent by late 1983" (p. 10). Del Giovane, Eramo, and Nobili (2011) state that "according to a literal reading of the banks' answers, the degree of tightening at the end of 2009 would be significantly higher than it was at the peak of the financial crisis" (p. 2729). Swiston (2008) and Bassett et al. (2014) have recently seen an increase in the number of easings, although

This is addressed by treating individual responses confidentially and distancing them from the supervisory department. However, loan officers can still avoid the truth or misinterpret the questionnaire, which makes statistical testing necessary.[13]

A distinctive feature of the survey is its breakdown of the four Italian areas.[14] Small banks report their qualitative supply-and-demand assessments for their single area of operation, while medium to large banks report multiple assessments, one for each region. Out of 5,481 observations, 2,071 are from banks with multiple assessments. The regional variation in the data can enhance the quality of comparisons with banks operating at different levels—small community and large national banks—and the control for confounding factors beyond supply and demand.[15]

The fact that the RBLS is a biannual survey also makes it an important source of information. Similar surveys are run quarterly and, while being biannual can be a limit, it adds to data quality. In fact, higher frequencies tend to reveal the (irrelevant) internal debate on future supply, in addition to the (relevant) policy in force. Moreover, biannual data can add to the debate over the lapse in time between the enactment of a supply change and the trace of its effect on loans.

At the core of both this work and the survey, there are two questions for the loan officer concerning the semi-annual change in credit standards[16] and in the demand for credit for non-financial corporations. The options are tightened considerably (−2), tightened somewhat (−1), basically unchanged (0), eased somewhat (1), and eased considerably (2) for supply; the options are decreased considerably (−2), decreased somewhat (−1), basically unchanged (0),

smaller than expected. In this regard, I notice that multiple minor changes in one direction can compensate for a strong change in the opposite direction.

[13]Testing survey data against different models represents a first and important step in this direction.

[14]They are better known as "macro areas." They are North-West, North-East, Center, and South and Islands.

[15]In this paper, multiple-area responses can be thought of as coming from different banks. I therefore use the term bank mostly to refer to a bank area.

[16]Credit standards shape the supply policy of a bank. Schreft and Owens (1991) argue that changes in the willingness to lend and changes in credit standards generally move together.

Table 1. Summary Statistics

	Mean	Std. Dev.	Min	Median	Max
Growth Rate, Loans ($\Delta L^{\%}_{i,a,t}$)	1.20	8.30	–71.82	0.51	95.55
Dummy, Sup. Tight. ($Sup^{tight}_{i,a,t}$)	0.35	0.48	0	0	1
Dummy, Sup. Easing ($Sup^{ease}_{i,a,t}$)	0.04	0.20	0	0	1
Dummy, Dem. Decrease ($Dem^{decr}_{i,a,t}$)	0.42	0.49	0	0	1
Dummy, Dem. Increase ($Dem^{incr}_{i,a,t}$)	0.23	0.42	0	0	1

Note: $\Delta L^{\%}_{i,a,t}$: half-yearly growth rates in percentage points (loans non-financial corporations). Dummies are equal to one in the event of a tightening (decrease) or easing (increase) in supply (demand) to non-financial corporations. 5,481 observations. 420 banks. Four areas. Between 2009:H1 and 2014:H1, an average of 375 banks are surveyed in each semester: 229 are mutual banks (small non-profit community banks) and 146 are non-mutual banks. The North-West and the North-East have an average of 286 reporting banks, the South and the Center 214.

increased somewhat (1), and increased considerably (2) for demand. The outcome of the two questions is matched with non-financial corporations loan data from the "Credit and Financial Institutions' Supervisory Reports" of the Bank of Italy, as they trace the equilibrium outcome of the market. All other balance sheet data are from that source. Outstanding loans to non-financial corporations include productive households, bad loans, and loans under a repurchase agreement. Bank-area loan growth rates are adjusted by the effects of securitizations, reclassifications, and other variations that are not a result of ordinary transactions, most notably mergers and takeovers (Appendix A).

Figure 1 and Table 1 show survey records in net percentages[17] and reveal the key features of the data. First, the 2009–14 period shows few easings and many tightenings in supply. Second, supply

[17]Net percentages show the number of banks changing their supply (or with a change in demand). The net percentage is the simple difference between the share of banks reporting a tightening (increase) in credit standards (demand) and the share of those reporting an easing (decrease). Although completely arbitrary, as pointed out in Bassett et al. (2014), positive values in net percentages are commonly considered as a proxy for an inward shift in supply (upward shift in demand).

and demand records are correlated (Appendix B). And third, supply changes in 39 percent of the occurrences.

3. Motivations for the Empirical Strategy

In this section, I set out the baseline econometric specification of this work. The aim is to use the new data set to discover the simplest model that can provide a consistent explanation of the functioning of the credit market. In fact, complex models can be used in future research and I show that they are not needed here, to test the information content of the new data set. In addition, complex models would also make the study of supply heterogeneity in the second part of this work less manageable. Accordingly, the baseline model of this work is the following:

$$\begin{aligned}\Delta L^{\%}_{i,a,t} = \mu + \alpha_{i,a} + \eta_{a,t} + \gamma Sem_t + \beta_1 Sup^{tight}_{i,a,t} + \beta_2 Sup^{ease}_{i,a,t} \\ + \beta_3 Dem^{decr}_{i,a,t} + \beta_4 Dem^{incr}_{i,a,t} + \varepsilon_{i,a,t}.\end{aligned} \tag{1}$$

$\Delta L^{\%}_{i,a,t}$ refers to the half-yearly growth rate of loans to non-financial corporations for bank i in area a at time t in percentage points. μ is an overall intercept. The model also features a full set of fixed effects. $\alpha_{i,a}$ denotes a bank-specific intercept that intends to capture self-reporting habits, portfolio composition effects, and other factors affecting the trends of loans for any given supply schedule. Note that multiple intercepts are allowed for banks operating in more than one area. $\eta_{a,t}$ refers to area-year fixed effects that control for the trend and structure of both the productive and financial sectors, thereby also accounting for borrowers' creditworthiness possibly changing both over time and across areas.[18] Sem_t is a seasonal dummy equal to 1 in the first semester of every year.

$Sup^{tight}_{i,a,t}$ is a binary indicator equal to 1 if bank i in area a at time t reports a tightening in its credit standards for non-financial

[18] Samolyk (1994) notes that the credit market is likely made up of sub-national markets. The creditworthiness of firms is assessed based on their balance sheets. As new and official balance sheet data are usually publicly available each year, area-year fixed effects should work better than area-semester fixed effects. However, large firm data are usually available at higher frequencies and firms' creditworthiness can also be affected by changes in the economic outlook. The two options are tested in Section 4: Table 2 shows that they are empirically equivalent.

corporations and $Sup^{ease}_{i,a,t}$ is a binary indicator for an easing. In turn, $Dem^{decr}_{i,a,t}$ is a binary indicator equal to 1 if bank i in area a at time t reports a decrease in the demand for loans from non-financial corporations and $Dem^{incr}_{i,a,t}$ is a binary indicator for an increase. Supply-and-demand decreases and increases are allowed to exert a different impact on lending, and this choice can only be evaluated by means of econometric analysis, which Section 4 does. Finally, $\varepsilon_{i,a,t}$ is the usual error term that closes the model. I now discuss three important points.

First, survey supply and demand records co-move over time. When addressing similar evidence for their survey, Bassett et al. (2014) argue that supply records are the confluence of supply and demand factors. By contrast, I see it as a possibly similar response to common shocks,[19] in line with Amiti and Weinstein (2018), for whom bank and firm shocks can indeed be correlated.[20]

Second, the literature relies more on survey supply records than on demand records. Nevertheless, demand records isolate the individual and specific demand for credit faced by each bank, in this paper even in each area of operation, and thus they control for the endogenous matching of banks and customers. Other proxies cannot control for the specific demand actually faced by each bank, thereby undermining the veracity of the results. On that issue, Altavilla et al. (2021) note that credit demand can vary not only at the firm level but also across banks, because several factors can induce a firm to opt for one bank or another.[21] Moreover, alternative variables cannot be accurately related either to supply or to demand. Del Giovane,

[19] Altavilla, Darracq Pariès, and Nicolletti (2015) argue that supply-and-demand net percentages are driven to a significant extent by common shocks over the business cycle. Lown and Morgan (2006) note that tighter standards could signal some negative disturbances in economic activity that also reduce loan demand.

[20] In this work both supply and demand variables are on the right-hand side of the estimating equation. This makes it possible to orthogonalize supply and demand. In fact, in the simple equation $y_i = \beta_1 x_i^1 + \beta x_i^2$, where x_i^1 is supply and x_i^2 demand, the ordinary least squares (OLS) estimator of β_1 is given by $\hat{\beta}_1 = \left(\sum_{i=1}^n \widehat{r_{i,1}} y_i\right)\left(\sum_{i=1}^n \widehat{r_{i,1}^2}\right)^{-1}$, where $\widehat{r_{i,1}}$ are the residuals of a simple regression of x_i^1 on x_i^2. Thus, the supply variation used to estimate β_1 is orthogonal to the demand for credit. Multicollinearity is not an issue in this work thanks to a favorable balance between supply-and-demand correlation and sample size.

[21] See Altavilla et al. (2021) for an excellent review of those factors.

Eramo, and Nobili (2011), for instance, additionally control for a number of macroeconomic variables "at the expense of a less immediate interpretation, since it is impossible to determine whether the part of credit developments explained by the control variables should be attributed to supply or to demand effects" (p. 2728). Some of the variables that can be found in the literature are gross domestic product (GDP) and various interest rates, business failure rates, excess bond premiums, and volatility indices. At the other extreme, Bassett et al. (2014) target supply innovations that originate from within the banking industry by controlling for as many factors as they can but discarding relevant and still genuine supply changes in response to external factors. As a consequence, I essentially rely on demand records, no macroeconomic variable enters my model, and the fixed effects are mostly intended to control confounding factors beyond supply and demand.[22]

Third, the RBLS tracks changes in supply and demand. This means that the RBLS provides no direct information on credit rationing, for which a knowledge of the level of supply and demand would be required. However, Bernanke and Lown (1991) note that "the notion that a macroeconomically significant credit crunch necessarily involves elements of credit rationing or a complete cutoff of some groups from credit is incorrect." If I discard the terms "significant" and "safe interest rate" from their definition of credit crunch, because they raise controversial issues, there emerges what the RBLS can most easily trace, namely "inward shifts in the supply curve for bank loans, holding constant both the overall demand of credit and the quality of potential borrowers."

As a final step, it is also worth highlighting two additional points. First, raw survey data are recoded into three wider categories: easing, tightening, unchanged and increase, decrease, unchanged.[23] Indeed, both as a cross-section and over time, what appears to be a strong change in the eyes of one loan officer may be seen as mild by

[22]Only the data will suggest if this is indeed the case.

[23]On the supply side, "tightened considerably" is grouped with "tightened somewhat," "eased considerably" with "eased somewhat," and "supply basically unchanged" remains in its original form. On the demand side, "decreased considerably" is grouped with "decreased somewhat," "increased considerably" with "increased somewhat," and "demand basically unchanged" also remains in its original form.

others.[24] However, the direction of the change, up or down, cannot be misunderstood. Finally, Holmstrom and Tirole (1997) argue that an increase in the net worth of companies should lead to a demand shift from bank loans to market bonds. This work focuses on bank loans, and the $Dem^{decr}_{i,a,t}$ dummy should account for this well-known fact: other relevant factors being equal, a major switch to the capital market should show up in a genuine decrease in the survey-reported demand for bank-intermediated credit.

4. How a Change in Supply Affects Lending: Estimation

I now present the estimates and I show that there is strong empirical evidence in favor of the arguments in the previous section. Table 2 shows dummy-variable OLS estimates of the relationship between supply dummies and the growth rate of loans. Those parameters are important because they show *how* supply, on average, affects lending. Table 2 indicates that the estimates are statistically significant and economically meaningful when all the relevant fixed effects are included. While column 1 includes no fixed effects and accounts poorly for the functioning of the credit market, column 2 allows for bank fixed effects and the tight-supply coefficient becomes statistically significant at the 5 percent level.[25] By contrast, column 3 shows that area fixed effects alone change the estimate much less. Instead, bank-area fixed effects in column 4 are critical, and column 5, with bank-area and area-year fixed effects, isolates the specific impact of supply better than any other specification. A comparison of columns 2, with only bank-area fixed effects, and 5, with also area-year fixed effects, shows that the demand-decrease coefficient

[24]Alternatively, loan officers may be less keen to report the truth on the details of the change. The "institutional memory hypothesis" of Berger and Udell (2004) may also be at work. In fact, memory loss of the internal process guiding the internal assessments of supply and demand can threaten the overall consistency of the survey. However, there are also reasons why the turnover of loan officers can affect data quality positively. In fact, Hertzberg, Liberti, and Paravisini (2010) find that loan officers have incentives to report truthfully when a rotation policy is in place.

[25]This contrasts with Del Giovane, Eramo, and Nobili (2011), where bank fixed effects are not critical. They state: "excluding bank fixed effects does not provide any significant change in the results" (p. 2724, footnote 12).

Table 2. OLS Estimates

	(1)	(2)	(3)	(4)	**Bench.** (5)	(6)
$Supply^{tight}$	–0.37	–0.77**	–0.37	–0.75**	–0.90***	–0.84***
	(0.2842)	(0.3516)	(0.2853)	(0.3526)	(0.3086)	(0.2909)
$Supply^{ease}$	–0.45	–0.19	–0.42	–0.11	0.25	0.23
	(0.8577)	(1.1040)	(0.8813)	(1.1619)	(1.1156)	(1.0627)
$Demand^{decr}$	–1.58***	–1.35***	–1.58***	–1.19***	–0.82***	–0.63*
	(0.3744)	(0.3217)	(0.3672)	(0.3629)	(0.3050)	(0.3210)
$Demand^{incr}$	2.92***	2.20***	2.88***	2.29***	1.68***	1.6682***
	(0.4559)	(0.4295)	(0.4493)	(0.4616)	(0.5028)	(0.4498)
n Observations	5,481	5,481	5,481	5,481	5,481	5,481
R^2	0.0469	0.2022	0.0497	0.2845	0.3165	0.3249
Pr > W[1]	—	0.0000	0.0000	0.0000	0.0000	0.0000
n Banks	420	420	420	420	420	420
n Areas	4	4	4	4	4	4
n Times	11	11	11	11	11	11
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	Yes	No	No	No	No
Area Fixed Effects	No	No	Yes	No	No	No
Bank-Area Fixed Effects	No	No	No	Yes	Yes	Yes
Area-Year Fixed Effects	No	No	No	No	Yes	No
Area-Semester Fixed Effects	No	No	No	No	No	Yes

Note: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$. Standard errors are in parentheses. Dependent variable: half-yearly growth rate of loans to non-financial corporations in percentage points. Dummy-variable OLS estimates. Standard errors clustered by bank and time. [1]*p-values* for the exclusion of fixed effects.

drops by 42 percent and the demand-increase coefficient by 24 percent. The tight-supply coefficient goes up by 17 percent and the ease-supply coefficient, although not statistically significant, critically turns positive. In column 5, the fixed effects are still jointly statistically significant and all but one of the coefficients are statistically significant at the 1 percent level. The estimate supports the arguments in Section 3, where the fixed effects were intended to control confounding factors beyond supply and demand. For this reason, column 5 in Table 2 is the benchmark estimate of this work.

In fact, column 5 in Table 2 reveals the explanatory power and the precision of the RBLS when at work with an appropriate model. Row 1 indicates that a tightening in supply leads to a significant decline of 0.90 percentage point in the half-yearly growth rate of loans. In turn, row 2 indicates that an easing in supply is associated with an upside acceleration of 0.25 point. Although the point estimate makes economic sense,[26] its standard error rises to the point that the effect is indistinguishable from zero, either because easings are rare in the sample or because they are particularly mild. Concerning demand controls, row 3 shows that a decrease in demand is associated with a slowdown in the dynamics of loans of 0.82 point,[27] and row 4 that an increase is associated with an upside acceleration of 1.68 points.

The difference between supply coefficients suggests that upside and downside changes in supply relate to the dynamics of loans asymmetrically. The supply-ease coefficient is not distinguishable from zero, whereas the supply-tight coefficient is robustly and statistically different from zero. The outcome shows the importance of accounting separately for upside and downside supply changes in order to follow their effect on loans properly.

Finally, I acknowledge that area-semester fixed effects could better control for any confounding factors relating to the change in credit quality of the pool of borrowers than area-year fixed effects.

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[26]Although not statistically significant, Del Giovane, Eramo, and Nobili (2011) always produce a negative sign for their easing coefficient.

[27]In contrast to Lown, Morgan, and Rohatgi (2000) and Del Giovane, Eramo, and Nobili (2011), all demand coefficients have the expected sign. Del Giovane, Eramo, and Nobili (2011) state: “quite often a negative BLS [the lending survey of the European Central Bank] demand indicator is associated with a largely positive change in loans” (p. 2729).

Although official firm balance sheet data are available each year, large firms commonly publish interim reports and firms' creditworthiness can also be affected by changes in the economic outlook. Column 6 in Table 2 shows that area-semester fixed effects produce insights that are almost indistinguishable from the ones with area-year fixed effects, the baseline for this work.

Overall, the estimate reveals that, when correctly understood, the RBLS provides valuable and precise additions to the understanding of the functioning of the credit market.

5. Robustness Checks

The statistical significance of the results is not sensitive to the clustering of the standard errors and, in the remaining part of the work, I rely on two-way clustering by bank and time (Appendix C). In addition, the main results of the benchmark model continue to hold when balancing the panel or by not including bad loans in the calculation of the growth rates of loans.[28]

Another well-known issue is the robustness of the results with regard to the dynamic persistence of loans, once changes in supply and demand occur. Indeed, broken lending relationships take time to be restored and a demand-driven decrease in loans can also affect the dynamics of loans in subsequent periods, as tranches of the same deal are not renewed. Agents' habits or perverse incentives can lead to "evergreen loans" or to additional reasons for the drifting of lending despite a new supply policy.[29] Column 5 in Table 3 shows the Arellano and Bover (1995) estimate of the dynamic version of the benchmark model that passes routine tests. Rows 3–6 show that the coefficients remain statistically significant. In addition, the coefficients on both lags of the dependent variable are positive and statistically significant, which shows that trends in the credit market do not revert immediately to former positions.[30] However, Table 3 also

[28]Results are available upon request. See also Appendix A.

[29]The argument is different from that in Lown and Morgan (2006), in which there is feedback from loans to credit standards.

[30]The result contrasts with Del Giovane, Eramo, and Nobili (2011), where the coefficient of the lagged dependent variable is not statistically significant in any of the specifications considered (p. 2722, footnote 10). Note that Del Giovane, Eramo, and Nobili (2011) work with quarterly data.

Table 3. Dynamic Models

	(1)	(2)	(3)	(4)	(5)	Bench. (6)
$\Delta L^{\%}_{t-1}$		–0.05	0.01	–0.05	0.09**	
		(0.0358)	(0.1253)	(0.0359)	(0.0356)	
$\Delta L^{\%}_{t-2}$			0.06		0.14***	
			(0.1536)		(0.0331)	
$Supply^{tight}$	–0.86***	–0.64***	–0.47*	–0.40*	–0.54**	–0.90***
	(0.2725)	(0.2405)	(0.2754)	(0.2336)	(0.2441)	(0.3086)
$Supply^{ease}$	0.50	0.36	0.75	–0.39	0.63	0.25
	(0.6464)	(0.7059)	(0.9083)	(0.6432)	(0.7196)	(1.1156)
$Demand^{decr}$	–0.61**	–0.48*	–0.47	–0.71**	–0.68**	–0.82***
	(0.2808)	(0.2638)	(0.3234)	(0.2773)	(0.2748)	(0.3050)
$Demand^{incr}$	1.04***	1.49***	1.62***	1.32***	1.46***	1.68***
	(0.3266)	(0.3544)	(0.3722)	(0.3680)	(0.3510)	(0.5028)
n Observations	4,780	4,535	4,321	5,147	4,907	5,481
Instruments	—	16	16	27	27	—
Test Wooldridge (*p-value*)	0.9030	—	—	—	—	—
Test Arellano-Bond (*p-value*)	—	0.6047	0.0186	0.9728	0.0333	—
Test Sargan (*p-value*)	—	0.8103	0.4667	0.3300	0.0006	—

Note: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Standard errors are in parentheses. Dependent variable: half-yearly growth rate of loans to non-financial corporations in percentage points. (1) Model with data in first-difference and no intercept. The Wooldridge (2002) test on data in first-difference shows a significant autocorrelation of –0.5 points. (2) (3) Arellano and Bond (1981) estimator. (4) (5) Arellano and Bover (1995) estimator. (2) (3) (4) (5) Two-step estimators corrected as in Windmeijer (2005). Arellano-Bond test: *p-values* are for the second lag. The Arellano-Bond test for error autocorrelation suggests introducing two lags for the dependent variable. The Sargan test suggests using one lag of the dependent variable as an instrumental variable. (6) Benchmark model. Dummy-variable OLS estimates.

reveals that the magnitude of the supply-tight coefficient falls from –0.90 to –0.54. A full accounting of the direct and indirect effects, the latter acting through the dynamic part of the model, reveals an overall supply contribution that is 0.40 percentage point smaller in the dynamic model.[31] Considering that the moderate time dimension of the sample challenges the accuracy of the dynamic estimate, I opted for the static model as the reference point for this work.

6. Further Robustness Checks

One additional concern is how loan officers interpret the questionnaire. Del Giovane, Eramo, and Nobili (2011) claim that the European Central Bank's (ECB's) lending survey can be better interpreted in relation to "some benchmark condition they [lending officers] are likely to have in mind" (p. 2731), and Swiston (2008) argues that loan officers are likely to report a tightening in supply during a period that is considered austere, regardless of whether a real change in supply has occurred. To test this hypothesis, I match the growth rate of loans with the first time-difference of survey indicators.[32] Following this transformation, two equally austere periods should cancel each other out, signaling the correct setup of supply. However, the hypothesis is rejected, because three out of four supply-and-demand coefficients are not statistically significant, supporting the view that a literal interpretation of the survey fits the developments of the market better (Appendix C).

Nevertheless, there is the option of using the cumulative sum of the changes. In fact, what occurred in the past may also be important for current lending, either because there is a difference between a first tightening and a further tightening or because the cumulative sum proxies the level of supply, which is perhaps more informative than its change. Del Giovane, Eramo, and Nobili (2011) show that the inclusion of the cumulative indicators provides unclear results, compromising the fit of their equations. By contrast, van der Veer

[31] The comparison is performed where the two models overlap, namely from 2011:H1 onwards, and by applying the technique described in Section 7.

[32] I used the first time-difference Δ, i.e., $x_t - x_{t-1}$, for each bank-area supply-and-demand dummy. In fact, in line with Swiston (2008), Schreft and Owens (1991) argue that "the survey's results are most meaningful when viewed relative to those from previous periods" (p. 33).

and Hoeberichts (2016) claim that the cumulative indicators provide valuable information. In my setting, the cumulative supply-and-demand indicators are mostly not statistically significant, supporting the view that their explanatory power is limited (Appendix C).

In addition, I also test the five-class version of the survey—see Section 3. Resorting to the original five-class form, the hypothesis that "strong" and "somewhat" coefficients have the same magnitude is not rejected. Moreover, the "strong decrease" coefficient is smaller than the "decreased somewhat" and the "strong easing" coefficient is negative and, oddly enough, statistically significant. The estimates are consistent with the view that what can appear as a strong change to one loan officer is at times seen as mild by others, threatening the internal consistency of the survey (Appendix C). Another critical factor is that the estimate of some specific types of change can be challenged by their lower occurrence in the sample. Indeed, a "strong easing" of supply only appears in 0.2 percent of the sample.

A key issue is also whether supply and demand need any time to pass before they affect loans, whereby lagged survey records can explain lending better. Swiston (2008) finds that credit standards pre-date most economic and financial data, while Bassett et al. (2014) argue that due to the reluctance of banks to make abrupt changes one can expect new strategies in credit standards to be implemented slowly.[33] A bank may also need time to fully implement a new strategy, and an increase in demand, although perceived by the loan officer, may need time to materialize. Unintentional misreporting can also play a role and lagged or even forwarded records may explain lending better. In fact, loan officers may report either what they observe when filling in the questionnaire or what they are discussing internally, namely the supply prospects for the near future. Moreover, loan officers can also report old changes in supply because hard information for the reference period is not yet available. As a consequence, I test different lag-and-forward combinations of survey indicators, including the scheme by Del Giovane, Eramo, and Nobili

[33] In Cunningham (2006), the lags of credit standards add to the prediction of loans. In Lown and Morgan (2006), credit standards still explain 18 percent and 28 percent of the variance of credit after four and eight quarters, respectively. De Bondt et al. (2010) show that credit standards lead business loans by four quarters. For an explanation of the change of credit standards within the context of bank management, see Luckett (1970).

(2011), namely lagged supply and contemporaneous demand. The estimates show that changing the timing of the indicators worsens the fit of my model and that the RBLS mostly produces coincident indicators (Appendix C).

7. Putting Together the Estimate of the Effect of a Supply Change with Actual Changes: From Individual to Market Data

I have so far established that changes in supply are both widespread and significant. Bank supply changes in 39 percent of the occurrences (Table 1) and lending decreases, on average, by 0.90 percentage point because of a tightening in supply (Table 2). This, however, does not necessarily translate into a significant change in the overall supply of credit at the market level. In fact, it is necessary to account for the bank-specific impact of each change and for any balance between tightening and easing. When doing so, it is useful to recognize that the observed growth rate of loans for bank i in area a at time t can be written as follows:

$$\begin{aligned}\Delta L^{\%}_{i,a,t} = \Delta L^{\%,0}_{i,a,t} &+ \left(\Delta L^{\%,1,tight}_{i,a,t} - \Delta L^{\%,0,tight}_{i,a,t}\right) Sup^{tight}_{i,a,t} \\ &+ \left(\Delta L^{\%,1,ease}_{i,a,t} - \Delta L^{\%,0,ease}_{i,a,t}\right) Sup^{ease}_{i,a,t}.\end{aligned} \tag{2}$$

The actual growth rate of loans for bank i in area a at time t $(\Delta L^{\%}_{i,a,t})$ is seen as the growth rate of loans in the absence of any change in supply $(\Delta L^{\%,0}_{i,a,t})$ plus the effect of any easings or tightenings $(\Delta L^{\%,1,x}_{i,a,t} - \Delta L^{\%,0,x}_{i,a,t})$. $Sup^{tight}_{i,a,t}$ and $Sup^{ease}_{i,a,t}$ are the usual binary indicators.

Starting from Equation (2), Appendix D easily shows that the overall contribution of supply is given by Equation (3) (x_1=$tight$, x_2=$ease$), where lagged lending $(L_{i,a,t-1})$ and the use of the simple growth rate of loans in the benchmark econometric model are both critical to guarantee consistency. The result is similar to Amiti and

Weinstein (2018) but applies to a different context and originates from a different setting.[34]

$$\underset{\text{contribution}}{\text{overall supply}} = \sum_{j=1,2} \left(\underbrace{\hat{\beta}_j}_{\substack{\text{how}\\ \text{much}}} \underbrace{\sum\nolimits_i \sum\nolimits_a^n Sup_{i,a,t}^{x_j}}_{\substack{\text{how}\\ \text{many}}} \underbrace{\frac{L_{i,a,t-1}}{\sum_i \sum_a^n L_{i,a,t-1}}}_{\substack{\text{individual impact}\\ \text{factor}}} \right) \tag{3}$$

Using Equation (3), Table 4 displays the best estimate of this paper of the overall contribution of supply to the dynamics of the Italian bank-intermediated business credit market between 2009 and 2014. With respect to 2008, actual lending declined by 4.41 percentage points. In the absence of any change in supply,[35] there would be a decline of 2.66 percentage points. Hence, the estimate suggests that approximately 40 percent of the overall decline in lending during the European sovereign debt crisis can be related to pure supply factors, i.e., 1.75 out of 4.41 percentage points.

8. The Time, Cross-Section, and Geographical Dimension of the New Survey

The regional detail is a distinctive feature of the new survey at the core of this work. No similar survey has so far been carried out asking banks to report data at the regional level, at least to my knowledge. To test the contribution of this feature of the data, I take advantage of the national supply-and-demand assessment provided by each bank along with regional data. Matching national survey data with bank lending at the national level produces the

[34]In relation to Amiti and Weinstein (2018), bank-area supply-and-demand data already factor in the formation and termination of lending relationships. Note that contrasting the no-bank with the all-banks tightening scenario would not be directly related to the research question of this study. Indeed, $\hat{\beta}_1$ itself can be interpreted as the difference in the aggregate dynamics of loans between those two hypothetical scenarios. Therefore, the supply-tight coefficient can also be understood as the contemporaneous market change in the dynamics of loans in one semester if *all* banks in *all* areas tightened their supply, with respect to the dynamics of loans in which *no* banks tightened their supply. Such an exercise would be a thought experiment and not an assessment of the actual overall supply contribution to the dynamics of loans.

[35]$\hat{\beta}_2$ is not distinguishable from zero and tightening is the only part relevant to the calculation.

Table 4. Overall Supply Contribution

	Actual Stock	Synthetic Stock	Supply Contributions
2009:H1	99.25	99.45	–0.20
2009:H2	98.30	98.34	–0.16
2010:H1	98.84	98.95	–0.07
2010:H2	100.78	101.02	–0.13
2011:H1	103.93	104.44	–0.26
2011:H2	103.17	104.06	–0.36
2012:H1	102.03	103.27	–0.34
2012:H2	100.74	102.11	–0.14
2013:H1	98.50	100.09	–0.26
2013:H2	96.07	97.76	–0.13
2014:H1	95.59	97.34	–0.08
Difference, 2014:H1 – 2009:H1	–4.41	–2.66	—
Difference, Actual – Synthetic	–1.75	—	—
Sum, Semesters	—	—	–2.13

Note: 2008:H2 stock of loans to non-financial corporations set to 100. Difference, 2014:H1 – 2009:H1: 2014:H1 stock of loans minus 2009:H1 stock of loans. Difference, Actual – Synthetic: 2014:H1 actual stock of loans minus 2014:H1 synthetic stock of loans. Sum, Semesters: sum of the supply contributions in each semester between 2009:H1 and 2014:H1. The actual dynamics of loans are based on total loans at the population level with growth rates adjusted (securitizations, reclassifications, and other variations that are not the result of ordinary transactions) at the national bank level. The exercise is performed using the four-digit supply tight coefficient –0.8959.

estimate in column 2 of Table 5. Unexpectedly, the supply-ease coefficient turns negative.[36] Furthermore, the supply-tight coefficient is no longer statistically significant at the 1 percent level and its magnitude falls considerably (–47 percent). Samolyk (1994) notes that the credit market is likely made up of local and sub-national markets, and the outcome suggests that national survey data can produce a bias estimate of the forces behind the credit market. Using the technique of Section 7 with national data, it would have resulted that

[36] As already noted in Section 4, the baseline estimate of this work produces a set of coefficients whose signs fully agree with economic theory. Although not statistically significant, Del Giovane, Eramo, and Nobili (2011), for instance, always produce a negative sign for their easing coefficient, which is at odds with economic theory.

Table 5. Breakdown by Time and Area

	Bench (Reg.)	National	North	South	Pre-2010:H2	Post-2010:H2	Pre-2011:H1	Post-2011:H1	Pre-2011:H2	Post-2011:H2	Pre-2012:H1	Post-2012:H1
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$Supply^{tight}$	–0.90***	–0.48**	–0.91***	–0.88†	–0.72*	–0.98***	–0.28	–1.41***	–0.73**	–1.11***	–0.67**	–1.36***
	(0.3086)	(0.1761)	(0.3121)	(0.5934)	(0.4235)	(0.3667)	(0.3980)	(0.4427)	(0.3670)	(0.4047)	(0.3420)	(0.5244)
$Supply^{ease}$	0.25	–0.10	0.3397	0.1118	–0.39	0.68	–0.03	0.52	–0.19	0.68	–0.30	0.86
	(1.1156)	(0.4655)	(0.7831)	(1.9932)	(1.2789)	(1.5486)	(1.1345)	(1.6596)	(1.0943)	(1.7155)	(1.0615)	(1.7613)
$Demand^{decr}$	–0.82***	–0.88***	–0.99***	–0.56	–1.50*	–0.48	–0.64	–0.89**	–1.30***	–0.31	–1.02**	–0.47
	(0.3050)	(0.2003)	(0.3666)	(0.4740)	(0.7870)	(0.3090)	(0.6080)	(0.3733)	(0.4687)	(0.4294)	(0.4097)	(0.4089)
$Demand^{incr}$	1.68***	1.70***	1.68***	1.71***	1.17	2.07***	1.88***	1.35**	1.62**	1.62**	1.78***	1.32**
	(0.5028)	(0.2429)	(0.6129)	(0.5290)	(0.7146)	(0.4809)	(0.6332)	(0.5653)	(0.6684)	(0.6350)	(0.5804)	(0.6030)
Wald Test of the Difference (p-values)												
$Supply^{tight}$				0.9727		0.5931		0.0114		0.3413		0.1835
$Supply^{ease}$				0.8932		0.5798		0.7732		0.6493		0.5503

Note: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. †The p-value for the statistical significance of this coefficient is 13.6 percent. Bank-time-area three-way clustering produces an estimate with a p-value that is well below 10 percent. Note, in fact, that when allowing for different coefficients between regions, it is highly plausible to consider the possibility that intra-region standard errors have a higher correlation than inter-region ones. One-way clustering by bank or area and bank-area two-way clustering also produce p-values below the 10 percent. Overall, the empirical evidence suggests that the point estimate for the tight coefficient in the South is a valid reference point, as least for the purpose of comparison between North and South when exploiting the technique of Section 7. Standard errors are in parentheses (two-way clustered by bank and time). Dependent variable: half-yearly growth rate of loans to non-financial corporations in percentage points. Benchmark model. National: bank and time fixed effects with seasonal dummy using national data, i.e., discarding the geographical breakdown available in the data. North: North-West and North-East. South: South and Center. Pre: the threshold is included in the first of the two sub-periods. The interaction terms are displayed side by side for ease of reading. Unbalanced panel of 420 banks.

supply contributes to 25 percent of the decline in lending, instead of 40 percent with regional data. Taken together, these results are consistent with the hypothesis that the regional variation in the data prevents the estimates from being biased, at least when dealing with a wide cross-section of diverse banks, as is the case in this new survey.

Furthermore, the baseline estimate in this work always produces the expected signs on demand coefficients. This constitutes an improvement in understanding the variation in the data with respect to what is commonly found in the literature. Del Giovane, Eramo, and Nobili (2011), for instance, note that a decline in their demand indicator is associated with a largely positive change in loans. A similar issue also arises in Lown, Morgan, and Rohatgi (2000). However, this improvement cannot be associated with the regional breakdown of the new data set. On the demand side, as shown in column 2 of Table 5, national estimates are almost unchanged with respect to the baseline regional estimate. That evidence supports the view that the improvement in understanding the variation in the data that can be seen in demand-side estimates likely originates from the large and unprecedented cross-section of banks in the new survey and shows that this literature commonly strikes a delicate balance between econometric model and data.

A regional survey constitutes a unique opportunity to test regional differences. The gap in economic development between North and South has been common in Italian history, with the South lagging behind. Thus, a logical level of aggregation uses banks' responses on the North-West and North-East against the ones on the South and Center to test any potential difference in the forces behind the equilibrium outcomes of the two areas. Using the estimates in column 3 and 4 of Table 5 with the technique in Section 7, I find that—notwithstanding the fact that the stock of loans declined less in the South than in the North of Italy—supply seems to make a higher contribution to the dynamics in the South. Seventy-two percent of the decline in lending in the South can be attributed to pure supply factors, against 28 percent in the North.[37]

[37]Note also that more banks changed supply in Northern than in Southern Italy in the first part of the period, while the opposite is true in the second part of the period (Appendix B).

Finally, Swiston (2008) argues that a shorter period minimizes the possibility of problems owing to structural breaks in any of the relationships in the data. The estimates in columns 5–12 of Table 5 use interaction dummies to allow the coefficients to vary over time. The estimates point to a sharp change from the second semester of 2011, in which banks significantly reduced their supply of credit. Calculations analogous to that in Section 7 show that 35 percent of the contribution that supply gave to the decline in lending is recorded in the 2009:H1–2011:H1 period. The remaining 65 percent is recorded in the 2011:H2–2014:H1 period. That difference originates from a significant increase in the magnitude of the change—in conjunction with a peak of the yield differential between Italian and German 10-year government bonds, a measure of the severity of crisis—and not from an increase in the number of banks that changed their supply, which occurred in the previous semester.

9. Exploring Heterogeneity in Bank Supply

Now that a model has been tested, it is possible to investigate supply heterogeneity by means of survey data. The exercise cannot be carried out with the same depth by other surveys, as they typically sample small to medium-sized groups of large banks. In doing so, I first allow different coefficients to banks assigned to different groups and then I resort to the Classifier Lasso estimator (C-Lasso) to group together banks with similar supply changes. Economic theory informs that capitalization, size, and liquidity are the main sources of financial constraint variation at the bank level,[38] and I study those factors using different variables. Governance and business model are other factors commonly debated in the literature, and I study those factors using several proxies.

9.1 Using Interaction Terms to Test Group Differences

In principle, I would like to retrieve *how* each bank changes supply to be put side by side with how many changes it makes, as directly reported in the survey. However, as in Maddala et al. (1997), some

[38] See, among others, Ashcraft and Campello (2007).

of the coefficients that I obtain from each bank have an unexpected sign and are difficult to interpret (Appendix E). Baltagi and Griffin (1997) point out that a time series cannot properly control for important features of the data, and Baltagi et al. (2003) argue that "in panel datasets with T up to 10, traditional homogeneous panel estimators would appear the only viable alternative" (p. 796).

Nevertheless, the heterogeneous supply behavior of banks is an interesting area of research not only in relation to a single bank but also in relation to groups of banks. In fact, a different number of banks in each group can decide to change supply, and they can also calibrate their changes differently. Accordingly, I use interaction terms to allow different coefficients to banks assigned to different groups.

First, I use the following classifications:

- FAREAS–MAREAS, namely the few (one, two) or many (three, four) areas in which a bank operates;
- NOGRU–GRU, namely the membership or non-membership of a bank in a banking group;
- NOTOP–TOP, namely the membership in a big (top five) banking group;[39]
- NOMUT–MUT, namely whether or not a bank is a mutual bank.[40]

Then, I study supply heterogeneity by means of balance sheet indicators, on which I calculate the average for 2005–06. The procedure aims to limit both endogeneity—early signs of financial distress date back to August 2007[41]—and data quality concerns, given that

[39]According to total funds intermediated.

[40]Mutual banks are small non-profit community banks.

[41]I am grateful to an anonymous referee for pointing out that the business models of the banks can be better appreciated with data far away from any event relating to the crisis. Taking, for instance, balance sheet data in 2010 would raise the issue of endogeneity: balance sheet data could be the result of the supply policy of banks, and not vice versa. By contrast, data back in, say, 2000 could provide an inaccurate representation of the business models banks had in force before the crisis. By using 2006–07 balance sheet data instead of 2005–06 balance sheet data, the main insights of this work are confirmed. However, the different distribution of the profitability indicators suggests that 2007 balance sheet data

one single year can record exceptional numbers. The indicators I use to classify banks as being above (A) or below (B) the median[42] are as follows:

- SIZE, logarithm of total assets;
- RISK, bad debts to total loans;
- CAP, capital and reserves to total assets;
- LIQ, cash and ECB deposits to total assets;
- FMIX, deposits and bank bonds over total loans;
- GBOND, government bonds over total assets;
- ROE, net profits over capital and reserves;
- EFF, gross income over personnel costs;
- TRA, net interest income over gross income.

Tables 6 and 7, with the procedure of Section 7, provide evidence of diverse lending behaviors between banks during the crisis (Figure 2). Group-members reduced their supply of credit more than stand-alone banks. Moreover, members of large banking groups changed their supply with greater intensity, with the result of greater tightenings in 2011 and 2012, as well as more generous easings in both 2013 and 2014. The evidence complements Beltratti and Stulz (2012), in which banks from countries with more restrictions on bank activities reduce loans less. In fact, banks belonging to a group usually run a wider range of activities and can be considered more exposed to a financial crisis because they are more connected to other financial players.

Concerning profit orientation, mutual banks reduced their overall supply less than other banks on account of the fact that the high share of mutual banks that changed their supply (Appendix G) is more than compensated by the mildness of their changes. Although

can already suffer from the early changes in market conditions that eventually gave rise to the crisis.

[42] The distribution of each indicator is shown in Appendix F. The exercise may read as follows: Did banks with different business models (SIZE, RISK, CAP, LIQ, FMIX, GBOND) before the crisis behave differently during the crisis? For each indicator, banks outside the 1st–99th percentiles are not used for the purpose of estimation. Cutting the tail of the distributions sharpens the statistical significance of the results when splitting the sample according to profit-and-loss indicators. After several robustness checks the 40th percentile replaces the median when dealing with TRA.

Table 6. Breakdown by Size, Group Membership, and Profit Orientation

	FAREAS (1)	**MAREAS (2)**	**NOGRU (3)**	**GRU (4)**	**NOTOP (5)**	**TOP (6)**	**NOMUT (7)**	**MUT (8)**
$Supply^{tight}$	–0.53**	–1.91**	–0.39	–1.61**	–0.76***	–2.76**	–1.31**	–0.49***
	(0.2307)	(0.8823)	(0.2676)	(0.6493)	(0.2607)	(1.3387)	(0.5938)	(0.1875)
$Supply^{ease}$	–0.34	0.82	0.95	–0.59	–0.09	2.49***	0.75	–0.50
	(0.3500)	(2.9006)	(1.2816)	(1.5101)	(1.2108)	(0.8805)	(1.9493)	(0.4469)
$Demand^{decr}$	–0.73***	–1.04	–0.95***	–0.64	–0.70**	–1.43	–0.74	–0.91***
	(0.2861)	(0.6891)	(0.3641)	(0.4918)	(0.3084)	(1.0954)	(0.5131)	(0.2692)
$Demand^{incr}$	1.73***	1.56	1.55***	1.86**	1.64***	1.98	1.92**	1.41***
	(0.3129)	(1.3493)	(0.5316)	(0.8528)	(0.5111)	(1.3131)	(0.8846)	(0.3528)
Wald Test of the Difference (p-values)								
$Supply^{tight}$		0.1121		0.0945		0.1135		0.1918
$Supply^{ease}$		0.6874		0.3974		0.0435		0.5201

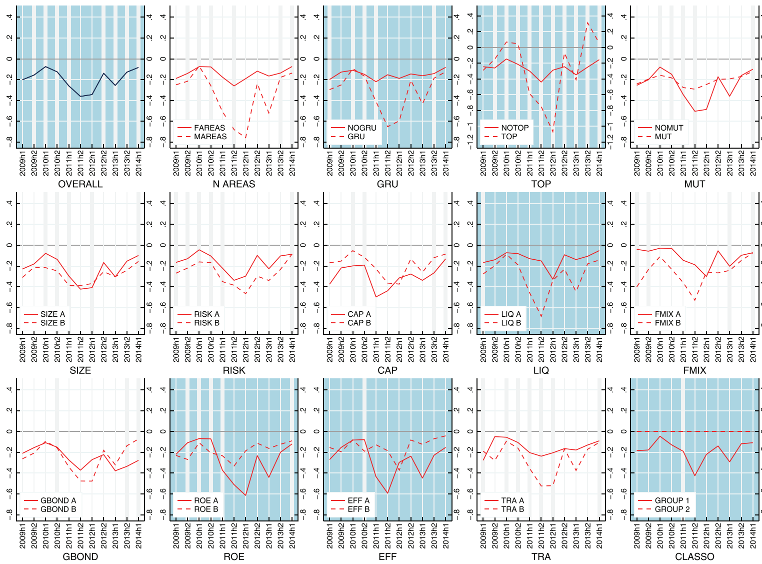
Note: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors are in parentheses (two-way clustered by bank and time). Dependent variable: half-yearly growth rate of loans to non-financial corporations in percentage points. Benchmark model. The interaction terms are displayed side by side for ease of reading. FAREAS: banks operating in one or two areas. MAREAS: banks operating in three or four areas. NOGRU: banks not in a banking group. GRU: banks in a banking group. NOTOP: banks not in one of the top five banking groups (according to funds intermediated). TOP: banks in one of the top five banking groups (according to funds intermediated). NOMUT: non-mutual banks. MUT: mutual banks (mutual banks are small non-profit community banks). Unbalanced panel of 420 banks.

Table 7. Breakdown by Balance Sheet Indicators

	SIZE-A	SIZE-B	RISK-A	RISK-B	CAP-A	CAP-B	LIQ-A	LIQ-B	FMIX-A	FMIX-B	GBOND-A	GBOND-B	ROE-A	ROE-B	EFF-A	EFF-B	TRA-A	TRA-B
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
$Supply^{tight}$	−1.07**	−0.68***	−0.85	−0.92**	−0.92***	−0.94*	−0.56	−1.38***	−0.62	−0.99*	−0.63***	−1.24**	−1.43***	−0.64*	−1.26***	−0.61**	−0.44**	−1.40**
	(0.5076)	(0.2496)	(0.5762)	(0.4470)	(0.3177)	(0.4934)	(0.4287)	(0.3616)	(0.3826)	(0.4959)	(0.2058)	(0.4930)	(0.4415)	(0.3287)	(0.4119)	(0.2957)	(0.2135)	(0.7041)
$Supply^{ease}$	1.81	−1.80	0.10	0.27	−0.28	0.53	1.38	−0.88	−0.39	0.89	−1.65	1.34	0.89	−0.11	0.44	−0.17	−1.57	1.82
	(1.5528)	(1.3732)	(0.8130)	(1.9329)	(0.6480)	(1.7863)	(1.6169)	(1.3717)	(1.8082)	(0.8792)	(1.3600)	(1.4677)	(0.5358)	(1.8503)	(1.2761)	(1.4818)	(1.0796)	(1.7186)
$Demand^{decr}$	−0.63	−0.68*	−0.82*	−0.50*	−0.67**	−0.77*	−0.86*	−0.56	−0.56	−0.97***	−0.93***	−0.49	−0.78**	−0.66*	−0.57**	−0.67	−0.60**	−0.80*
	(0.3853)	(0.3953)	(0.4977)	(0.2730)	(0.3207)	(0.4232)	(0.4454)	(0.4242)	(0.4175)	(0.3380)	(0.3104)	(0.3920)	(0.3889)	(0.3809)	(0.2495)	(0.4148)	(0.2962)	(0.4718)
$Demand^{incr}$	1.40**	1.99***	1.72**	1.77**	2.12***	1.46*	1.45**	1.86***	2.48***	1.01*	1.54***	1.85***	1.46**	1.97***	1.58***	2.04***	1.83***	1.72*
	(0.6791)	(0.6218)	(0.6908)	(0.6971)	(0.3534)	(0.8775)	(0.5926)	(0.7027)	(0.6819)	(0.5234)	(0.4631)	(0.7064)	(0.7214)	(0.7413)	(0.5102)	(0.7185)	(0.3411)	(0.9586)
Wald Test of the Difference (p-values)																		
$Supply^{tight}$		0.4905		0.9323		0.9705		0.0880		0.5414		0.2332		0.0884		0.0814		0.1834
$Supply^{ease}$		0.0756		0.9262		0.6662		0.2387		0.4705		0.1151		0.5938		0.7103		0.0729

Note: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$. Standard errors are in parentheses (two-way clustered by bank and time). Dependent variable: half-yearly growth rate of loans to non-financial corporations in percentage points. Estimates by above (A) and below (B) median balance sheet indicators (for TRA the 40th percentile replaces the median). Balance sheet classification is performed according to the 2005–06 average. For two banks some balance sheet data refer to 2007. Benchmark model. The interaction terms are displayed side by side for ease of reading. The outcome is robust to using banking-group-level data. SIZE: logarithm of total assets. RISK: bad debts to total loans. CAP: equity to total assets. LIQ: cash and ECB deposits to total assets. FMIX: deposits and bank bonds over total loans. GBOND: government bonds over total assets. ROE: net profit over equity. EFF: gross income over personnel costs. TRA: net interest income over gross income. Unbalanced panel of 413 banks.

Figure 2. Diverse Lending Behaviors between Banks during the Crisis



Note: Overall supply contributions to the dynamics of loans to non-financial corporations (percentage points; this quantity parallels the last column of Table 4 in Section 7; see Appendix D). A dark plot region refers to the statistical significance of the difference in supply coefficients (at least 10 percent). Tight or easing coefficients must be different between groups, and at least one must be distinguishable from zero. Tight coefficients are used at face value. Easing coefficients are set to zero with the exception of TOP. The C-Lasso estimator identifies two groups of banks with different supply-and-demand coefficients. Thick vertical lines indicate statistical significance (at least 10 percent) of the difference in the net percentages (two-sided Welch test). The supply net percentage is the simple difference between the share of banks reporting a tightening in credit standards and the share of those reporting an easing. To avoid mechanical differences between groups due to their size, the weighting scheme works inside each group. First part: FAREAS: banks operating in one or two areas. MAREAS: banks operating in three or four areas. NOGRU: banks not in a banking group. GRU: banks in a banking group. NOTOP: banks not in one of the top five banking groups (according to funds intermediated). TOP: banks in one of the top five banking groups (according to funds intermediated). NOMUT: non-mutual banks. MUT: mutual banks (mutual banks are small non-profit community banks). Unbalanced panel of 420 banks. Second part: overall supply contributions by above (A) and below (B) median balance sheet indicators of the banks (for TRA the 40th percentile replaces the median). Balance sheet classification is performed according to the 2005–06 average. For two banks, some balance sheet data refer to 2007. The outcome is robust to using banking-group-level data. SIZE: logarithm of total assets. RISK: bad debts to total loans. CAP: capital and reserves to total

(*continued*)

Figure 2. (Continued)

assets. LIQ: cash and ECB deposits to total assets. FMIX: deposits and bank bonds over total loans. GBOND: government bonds over total assets. ROE: net profit over capital and reserves. EFF: gross income over personnel costs. TRA: net interest income over gross income. Unbalanced panel of 413 banks. Third part: overall supply contributions by C-Lasso groups. Group 1 supply contributions are almost always zero due to light-handed changes in supply, not to the absence of supply changes. Balanced panel of 301 banks.

the evidence can reconcile contrasting views on the role of mutual and non-mutual banks in the years 2009–14, the large but statistically insignificant difference in supply coefficients in Table 6 does not allow for a robust conclusion.

As shown in Table 7, the size of a bank is not a distinctive feature that characterizes the business model of the banks that behaved differently during the crisis. By also using the first and third percentile of the distribution of size to account for banks that are either particularly small or big, a standard concern in the literature, the outcome is virtually unchanged.

Interestingly, banks that entered the 2009–14 period with less cash and ECB deposits to total assets reduced their supply of credit more (Figure 2). This can be explained by the liquidity stress of the crisis. The position in government bonds provides similar but less clear-cut evidence, consistent with the view that government bonds can only partially substitute cash. Furthermore, from 2011 to 2014 banks with greater profits before the crisis reduced their supply more than less profitable banks. From 2009 to 2011, the low number of banks that changed their supply (Appendix G) offset the considerable size of their changes, with the possible interpretation that their profitability was related to a latent risk that materialized later on during the crisis. The finding is similar to Beltratti and Stulz (2012), in which banks with good performances had lower returns before the global financial crisis. The overall contribution of supply is also larger for banks with higher efficiency, because of the large size of their changes and probably owing to an efficiency-correlated ability to change their supply in a more controlled and effective way.

Adding to a well-known debate, banks that entered the 2009–14 period with different capital positions do not show any significant difference in their supply behavior, and this also holds true when using the tier 1 ratio or the tangible common equity ratio as alternative measure of banks' distance from regulatory insolvency.[43]

9.2 Using the Classifier Lasso Estimator to Uncover Hidden Heterogeneity

Although it is common practice, assigning banks to different groups can be a poor exercise for two reasons. On the one hand, there is the assumption that the group classification is fully known according to a number of different external classifications, an assumption that is questionable in many respects. On the other hand, alternating single indicators is a process that neglects important balance sheet interactions.[44] I therefore use the Classifier Lasso (C-Lasso) penalized profile likelihood estimator of Su, Shi, and Phillips (2016). This estimator is able to achieve simultaneous classification and consistent estimation in a single step by shrinking individual coefficients to the unknown group-specific coefficients. In other words, the C-Lasso makes multiple individual and group estimates in order to group banks that change supply in a similar way. Once the C-Lasso classifies the banks (Appendix H), I can analyze their overall supply pattern, composition, and balance sheet configuration.

Interestingly, I find two groups of banks. The supply-tight coefficient of the first group is statistically different from zero at the 1 percent confidence level, whereas the supply-tight coefficient of the second group is not statistically significant (Table 8). The latter is also small and only marginally below zero, signaling exceptionally mild supply changes. As a consequence, I find that the first group of banks reduced its overall supply of credit more than the second group (Figure 2).

Most of the results in the previous subsection are confirmed, as shown in Table 9. However, the differences between the two groups of banks are statistically significant for group membership and income

[43]Tier 1 ratio: regulatory capital to total risk-weighted assets. Tangible common equity ratio: capital and reserves minus preferred stock and intangible assets to total assets minus intangible assets.

[44]Bonaccorsi di Patti and Sette (2016) argue that the level of capital can influence the elasticity of lending to liquid assets (p. 9 of the working paper version). See also Kapan and Minoiu (2013). As shown in Appendix F, balance sheet indicators are significantly correlated.

Table 8. C-Lasso Estimates

	Group 1	Group 2
	(1)	**(2)**
$Supply^{tight}$	–2.53***	–0.00
	(0.8139)	(0.2745)
$Supply^{ease}$	0.00	0.19
	(1.7400)	(1.6905)
$Demand^{decr}$	–1.52***	–0.01
	(0.4199)	(0.3134)
$Demand^{incr}$	0.00	3.32***
	(1.0840)	(0.5602)

Note: $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors are in parentheses (two-way clustered by bank and time). Bootstrap standard errors provide similar results. Dependent variable: half-yearly growth rate of loans to non-financial corporations in percentage points. Post–C-Lasso estimates with non-standardized variables. Post–C-Lasso estimates with standardized variables produce similar results. Benchmark model. Balanced panel of 301 banks.

origination. In fact, in the first group, there are more banks that belong to a banking group and the net interest income tends to be a lower share of their total income. The evidence is similar to Demirgüç-Kunt and Huizinga (2010), in which banks relying more on non-interest income increase their fragility. In fact, non-interest income is a more volatile source of revenue than interest rate income and is thus considered a riskier source of income. Therefore, I find that group-members with a less traditional commercial business model, at least as suggested by their lower dependence on interest income, reduced their supply of credit to firms more than other banks.

10. Final Remarks

In adding to the debate on the slowdown in business loans during the European sovereign debt crisis and on the information content of lending surveys, I find that a literal interpretation of the new Regional Bank Lending Survey (RBLS) consistently fits the developments in the Italian bank-intermediated business credit market in

Table 9. Composition and Balance Sheet Indicators by C-Lasso Groups

Composition				Balance Sheet			
	Group 1 (1)	Group 2 (2)	*p-values*		Group 1 (3)	Group 2 (4)	*p-values*
MAREAS	0.267	0.231	0.224	SIZE	6.7765	6.5169	0.131
GRU	0.444	0.363	0.064*	RISK	0.0221	0.0221	0.507
TOP	0.126	0.120	0.430	CAP	0.0856	0.0855	0.516
MUT	0.519	0.560	0.223	LIQ	0.0054	0.0055	0.430
				FMIX	1.1563	1.1248	0.131
				GBOND	0.1132	0.1010	0.399
				ROE	0.0926	0.0886	0.399
				EFF	2.8156	2.7752	0.246
				TRA	0.6748	0.6876	0.045**

Note: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Composition: mean. One-sided Welch test. MAREAS: dummy equal to one for operations in three or four area. GRU: dummy equal to one for banking-group membership. TOP: dummy equal to one for top-five banking-group membership. MUT: dummy equal to one for mutual banks (mutual banks are small non-profit community banks). Two-sided tests produce similar results but statistical significance for GRU is lost. Balance sheet indicators: median, 2005–06 average. For two banks some balance sheet data refer to 2007. *p-values* are from a non-parametric test of equality of medians, one-sided Fisher exact (values equal to the median assigned to below group). SIZE: logarithm of total assets. RISK: bad debts to total loans. CAP: equity to total assets. LIQ: cash to total assets. FMIX: deposits and bank bonds over total loans. GBOND: government bonds over total assets. ROE: net profit over equity. EFF: gross income over personnel costs. TRA: net interest income over gross income. The outcome is robust to using banking-group-level data. The ratio of net interest income over total assets produces similar insights to TRA but with an even higher statistical significance (1 percent). Two-sided tests produce similar results. Balanced panel of 301 banks.

the years 2009–14. Its unique regional breakdown and wider cross-section of banks also improve our understanding of the variation in the data. Properly aggregated survey records show that pure supply factors account for approximately 40 percent of the decline in lending, i.e., 1.75 out of 4.41 percentage points. Credit supply declined substantially from the second semester of 2011 and seems to play a greater role in the South of the country.

The banks that reduced their supply of credit more than other banks are less liquid but efficient and profitable. They are also more connected to other financial players because they tend to belong to a banking group. In addition, when they belong to a large group, their supply pattern is significantly different from other banks, with greater tightenings and easings.

An alternative estimator selects group membership and a lower dependence on interest income as the principal factors that negatively affect the supply of credit during the crisis, namely banks with a possibly less traditional commercial business model.

Thus, the empirical evidence in this work adds to the debate over the functioning of the credit market during a period of crisis and can inform central bankers' future policy action. The paper also has important implications for the management of lending surveys that, if properly understood, provide policymakers with valuable and precise information.

Appendix A. On Bank Lending Activity and Loan Growth Rates

In this paper, credit quantities refer to the growth rate of outstanding loans as in Del Giovane, Eramo, and Nobili (2011). Bassett et al. (2011) argue for the use of fully decomposed lending flows.[45] However, data availability represents a constraint. Bassett et al. (2014) match SLOOS[46] data with the sum of outstanding loans (on balance sheet) and unused commitments (off balance sheet). Similarly,

[45] Bassett et al. (2011) state that "information on drawdowns, credit line expirations, and bank- or borrower-induced reductions or cancellations of credit lines is also crucial to any effort that attempts to monitor bank lending capacity during a cyclical downturn."

[46] The SLOOS is a lending survey carried out by the Federal Reserve System.

Bonaccorsi di Patti and Sette (2016)[47] use committed credit. Bonaccorsi di Patti and Sette (2016) claim that their measure reflects bank supply more. In this paper, outstanding loans are (i) a measure that does not exclude loans below €30,000 as committed credit would do; (ii) a measure that might provide lower bound estimates for the contribution of supply, at least according to Bonaccorsi di Patti and Sette (2016); (iii) a measure that is convenient, as it is closely monitored by the Bank of Italy; and (iv) a measure that is highly correlated with committed credit, as shown in Bassett et al. (2014) and Bonaccorsi di Patti and Sette (2016).

The bank-area growth rate of loans is adjusted by the effects of securitizations, reclassifications, and other variations not due to ordinary transactions—most notably, mergers and takeovers. The procedure works on a monthly basis. If the acquired bank shuts down in the month of the deal, the acquiring bank-area growth rates are corrected by the acquired bank areas' latest reported loans. If this is not the case, when the acquired bank areas' outstanding loans fall more than 80 percent, the acquiring bank-area growth rate will be adjusted, and the acquired bank-area growth rate neutralized. Remember that the correction works on a monthly basis and half-yearly data are then used in the analysis. However, a few bank-area loan growth rates still show exceptional variations, likely relating to single client events, to new market entries (or exits) from marginal areas, or to data issues. The estimates discard growth rates with an absolute value greater than 100 percent. Some 18 out of 5,499 observations drop out of the sample, but no bank exits the analysis altogether. The main results of this work continue to hold when (i) setting a threshold of 150 points; (ii) dropping Cook-distant observations according to a $4/n$ cutoff (n represents the total number of observations); (iii) dropping the maximum and the minimum growth rates in each area half-yearly; and (iv) working with raw data.

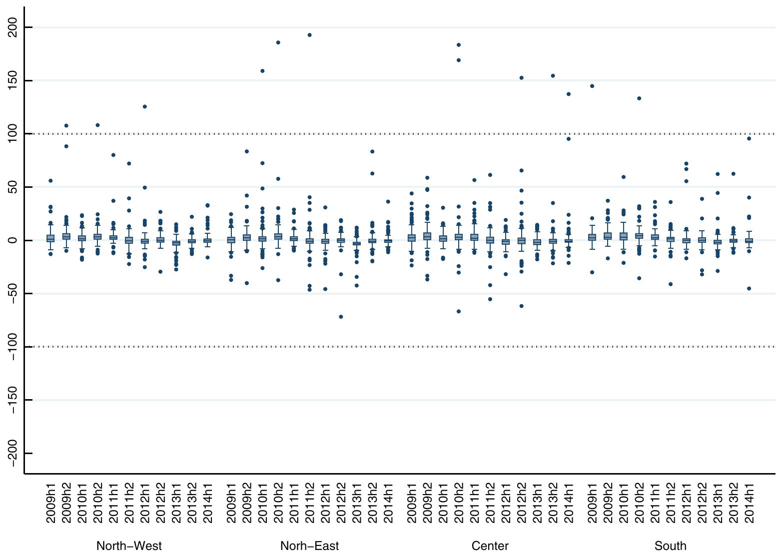
It is also important to address the issue of bad loans, which are included in the analysis for several reasons. First, subtracting bad loans could suggest trends relating neither to supply nor to demand. Second, the time frame in which good loans become bad

[47] On this subject, consider the working paper version of their study.

loans is idiosyncratic. Third, the European System of Central Banks methodology for calculating loan growth rates does include bad loans. However, their relevance needs to be evaluated by means of econometric analysis. Thus, the benchmark model is also estimated by subtracting bad loans from outstanding loans. The results, available upon request, parallel the ones in Table 2 of Section 4, showing that bad loans are not an issue for this work.

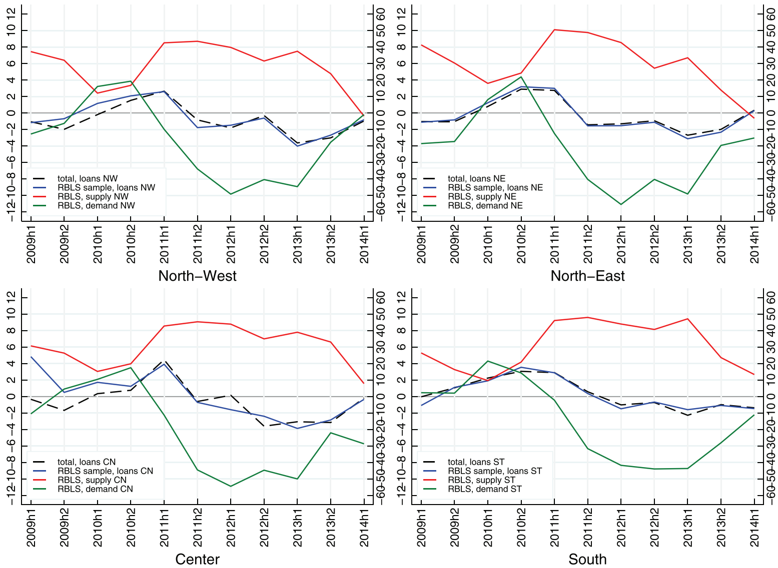
Appendix B. Data

Figure B.1. Individual Bank-Area Data



Note: Loans to non-financial corporations by area (RBLS sample) before dropping values above 100 in absolute value. Individual half-yearly growth rates (percentage points): box plot with outside values. Five observations are out of range.

Figure B.2. Loans to Non-financial Corporations and RBLS Indicators for Non-financial Corporations



Note: Loans to non-financial corporations (left-hand scale, percentage points, half-yearly growth rates adjusted—securitizations, reclassifications, and other variations that are not a result of ordinary transactions—at the area-bank level) and RBLS indicators (right-hand scale, net percentages) for non-financial corporations. RBLS: net percentages, positive (negative) values of the RBLS supply indicator reflect a tightening (easing) in supply; positive (negative) values of the RBLS demand indicator reflect an increase (decrease) in demand. The net percentage is the simple difference between the share of banks reporting a tightening (increase) in credit standards (demand) and the share of those reporting an easing (decrease).

Table B.1. RBLS Survey Records: Correlations

	$Dem^{incr}_{i,a,t}$	$Dem^{incr}_{i,a,t-1}$	$Dem^{incr}_{i,a,t-2}$	$Dem^{incr}_{i,a,t-3}$	$Dem^{decr}_{i,a,t}$	$Dem^{decr}_{i,a,t-1}$	$Dem^{decr}_{i,a,t-2}$	$Dem^{decr}_{i,a,t-3}$	$Sup^{ease}_{i,a,t}$	$Sup^{ease}_{i,a,t-1}$	$Sup^{ease}_{i,a,t-2}$	$Sup^{ease}_{i,a,t-3}$	$Sup^{tight}_{i,a,t}$	$Sup^{tight}_{i,a,t-1}$	$Sup^{tight}_{i,a,t-2}$	$Sup^{tight}_{i,a,t-3}$
$Sup^{tight}_{i,a,t}$	−0.0883*	−0.0157	0.0949*	0.1201*	0.1947*	0.0880*	−0.0484*	−0.0815*	−0.1577*	−0.0683*	−0.0031	0.0203	1			
$Sup^{tight}_{i,a,t-1}$	−0.0577*	−0.0974*	−0.0068	0.0908*	0.1178*	0.2147*	0.0628*	−0.0571*	−0.0625*	−0.1380*	−0.0537*	0.0017	0.3730*	1		
$Sup^{tight}_{i,a,t-2}$	−0.0420	−0.0585*	−0.0913*	−0.0088	0.0689*	0.1212*	0.1986*	0.0432*	0.0085	−0.0310	−0.1274*	−0.0427	0.2169*	0.3645*	1	
$Sup^{tight}_{i,a,t-3}$	0.0273	−0.0322	−0.0520*	−0.0779*	0.0109	0.0698*	0.1028*	0.1893*	0.0830*	0.0571*	−0.0114	−0.1309*	0.1302*	0.2077*	0.3159*	1
$Sup^{ease}_{i,a,t}$	0.1628*	0.0297	−0.0030	−0.0196	−0.0997*	−0.0390	0.0197	0.0349	1							
$Sup^{ease}_{i,a,t-1}$	0.1312*	0.1402*	0.0063	0.0191	−0.1087*	−0.0741*	0.0014	0.0200	0.3330*	1						
$Sup^{ease}_{i,a,t-2}$	0.0450*	0.1170*	0.1222*	0.0185	−0.0812*	−0.0896*	−0.0804*	−0.0170	0.0814*	0.2647*	1					
$Sup^{ease}_{i,a,t-3}$	0.0099	0.0488*	0.1056*	0.1239*	−0.0417	−0.0823*	−0.0797*	−0.0848*	−0.0122	0.0517*	0.2407*	1				
$Dem^{decr}_{i,a,t}$	−0.4441*	−0.1985*	−0.1142*	−0.0219	1											
$Dem^{decr}_{i,a,t-1}$	−0.2113*	−0.4475*	−0.1932*	−0.1204*	0.3521*	1										
$Dem^{decr}_{i,a,t-2}$	−0.1276*	−0.1976*	−0.4646*	−0.2159*	0.2039*	0.3297*	1									
$Dem^{decr}_{i,a,t-3}$	−0.0231	−0.1150*	−0.1994*	−0.4857*	0.0410	0.1864*	0.3324*	1								
$Dem^{incr}_{i,a,t}$	1															
$Dem^{incr}_{i,a,t-1}$	0.3598*	1														
$Dem^{incr}_{i,a,t-2}$	0.2042*	0.3219*	1													
$Dem^{incr}_{i,a,t-3}$	0.0901*	0.2070*	0.3235*	1												

Note: Listwise correlations. $*p < 0.01$. $Sup^{tight}_{i,a,t}$ is a binary indicator for a tightening in the credit standards, $Sup^{ease}_{i,a,t}$ is a binary indicator for an easing in credit standards, $Dem^{decr}_{i,a,t}$ is a binary indicator for a decrease in the demand for credit, and $Dem^{incr}_{i,a,t}$ is a binary indicator for an increase in the demand for credit.

Appendix C. Robustness Checks

Table C.1. Clustering the Standard Errors of the Baseline Model Estimate

	Coef.	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Supply^{tight}$	–0.90	(0.2583)***	(0.2406)***	(0.2729)***	(0.2951)***	(0.2823)***	(0.2789)***	(0.3086)***
$Supply^{ease}$	0.25	(0.5585)	(0.8106)	(0.9354)	(1.0520)	(0.9714)	(0.7256)	(1.1156)
$Demand^{decr}$	–0.82	(0.2654)***	(0.2588)***	(0.2865)***	(0.3281)**	(0.2501)***	(0.2082)***	(0.3050)***
$Demand^{incr}$	1.68	(0.3064)***	(0.3400)***	(0.3878)***	(0.4566)***	(0.4279)***	(0.4872)***	(0.5028)***

Note: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors are in parentheses. Dependent variable: half-yearly growth rate of loans to non-financial corporations in percentage points. Dummy-variable OLS estimates. Benchmark model. Heteroskedasticity is not rejected by a Breusch-Pagan test. (1) Spherical standard errors. (2) Standard errors robust to heteroskedasticity. (3) Standard errors clustered by bank area. (4) Standard errors clustered by bank. (5) Standard errors clustered by time. (6) Non-parametric standard errors as in Driscoll and Kraay (1998). Bandwidth set to 1. Although this technique does not require any prior knowledge of the exact form of the contemporaneous and lagged cross-unit correlations, Monte Carlo evidence points to a downward bias when dealing with a short time series. (7) Two-way standard errors by bank and time. Unbalanced panel of 420 banks. Two-way exercise follows Thompson (2011), with the additional correction of Cameron, Gelbach, and Miller (2011). I make use of the material in Petersen (2009) to run the two-way exercise.

Table C.2. Further Robustness Checks

	Bench. (1)	**(2)**	**(3)**	**(4)**
$Supply^{tight}$	–0.90***			
$Supply^{ease}$	0.25			
$Demand^{decr}$	–0.82***			
$Demand^{incr}$	1.68***			
$\Delta Supply^{tight}$		–0.14		
$\Delta Supply^{ease}$		0.67		
$\Delta Demand^{decr}$		–0.15		
$\Delta Demand^{incr}$		0.61***		
$\Sigma_{j=1}^{t} Supply_j^{tight}$			–0.42**	
$\Sigma_{j=1}^{t} Supply_j^{ease}$			0.85	
$\Sigma_{j=1}^{t} Demand_j^{decr}$			–0.07	
$\Sigma_{j=1}^{t} Demand_j^{incr}$			–0.12	
$Supply^{tight-strong}$				–1.60**
$Supply^{tight-somewhat}$				–0.88***
$Supply^{ease-strong}$				–6.90*
$Supply^{ease-somewhat}$				0.50
$Demand^{decr-strong}$				–0.44
$Demand^{decr-somewhat}$				–0.80**
$Demand^{incr-strong}$				6.02***
$Demand^{incr-somewhat}$				1.29***
n Observations	5,481	4,771	4,789	5,481
R^2	0.3165	0.2498	0.2836	0.3226

Note: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$. Standard errors are two-way clustered by bank and time. Dependent variable: half-yearly growth rate of loans to non-financial corporations in percentage points. Baseline setting with bank-area fixed effects, area-year fixed effects, and seasonal dummy.

Table C.3. Distributed Lag Models

	Bench. (1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
$Supply^{tight}$	–0.90***			–0.29		–0.89***	–0.75***	
$Supply^{ease}$	0.25			0.31		–1.01	0.63	
$Demand^{decr}$	–0.82***			–0.56***		–0.89***		–1.00***
$Demand^{incr}$	1.68***			1.93***		1.62***		1.77***
$Supply^{tight}_{t-1}$		–0.26		–0.18				–0.35
$Supply^{ease}_{t-1}$		–0.87		–1.17*				–1.03
$Demand^{decr}_{t-1}$		–0.66***		–0.30			–0.68***	
$Demand^{incr}_{t-1}$		0.56*		0.43			0.52	
$Supply^{tight}_{t-2}$			–0.17	–0.03				
$Supply^{ease}_{t-2}$			0.23	0.25				
$Demand^{decr}_{t-2}$			0.00	0.03				
$Demand^{incr}_{t-2}$			0.12	0.15				
$Supply^{tight}_{t+1}$					0.26	0.43*		
$Supply^{ease}_{t+1}$					–0.08	0.14		
$Demand^{decr}_{t+1}$					–0.45	–0.30		
$Demand^{incr}_{t+1}$					0.95*	0.80		
n Observations	5,481	4,789	4,254	4,191	4,784	4,784	4,789	4,789
R^2	0.3165	0.2843	0.2711	0.2876	0.2890	0.3022	0.2875	0.2942

Note: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors are two-way clustered by bank and time. Dependent variable: half-yearly growth rate of loans to non-financial corporations in percentage points. Benchmark setting with bank-area fixed effects, area-year fixed effects, and seasonal dummy.

Appendix D. The Aggregation Exercise: Technical Note

This section describes a computationally parsimonious procedure to assess the *overall contribution of supply* at the market level. It also provides the rationale for weighting survey indicators with lagged outstanding loans. Without losing generality, the focus is on one point in time, t, and changes are always intended over $t-1$.

$\Delta L^{\%}_{i,a,t}$ is the percentage growth rate of loans by bank i in area a at time t. $\Delta L^{\%}_{t}$ is the country-wide percentage growth rate of loans. $\Delta L_{i,a,t}$ and ΔL_t are the changes in outstanding loans, and $L_{i,a,t}$ and L_t their levels. $\Delta L^{\%,0,tight}_{i,a,t}$ is the percentage growth rate of loans by bank i in area a as it would be at time t if bank i did not tighten its supply, irrespective of whether it actually tightened it. $\Delta L^{\%,1,tight}_{i,a,t}$ is the percentage growth rate of loans by bank i in area a as it would be at time t if bank i tightened its supply, irrespective of whether or not it actually tightened it. $\Delta L^{\%,0,ease}_{i,a,t}$ is the percentage growth rate of loans by bank i in area a as it would be at time t if bank i did not ease its supply, irrespective of whether it actually eased it. $\Delta L^{\%,1,ease}_{i,a,t}$ is the percentage growth rate of loans by bank i in area a as it would be at time t if bank i eased its supply, irrespective of whether it actually eased it. $\Delta L^{\%,0}_{i,a,t}$ is the percentage growth rate of loans by bank i in area a as it would be at time t if bank i did not ease or tighten its supply, irrespective of whether it actually eased or tightened it. A similar interpretation applies to the remaining piece of notation. The benchmark model is shown in Equation (D.1). $Sup^{tight}_{i,a,t}$ is a binary indicator equal to 1 when bank i in area a at time t tightens its supply and $Sup^{ease}_{i,a,t}$ is a binary indicator equal to 1 in case bank i in area a at time t eases its supply. N is the population size, n the sample one (banks times areas).

$$\begin{aligned}\Delta L^{\%}_{i,a,t} = \mu + \alpha_{i,a} + \eta_{a,t} + \gamma Sem_t + \beta_1 Sup^{tight}_{i,a,t} + \beta_2 Sup^{ease}_{i,a,t} \\ + \beta_3 Dem^{decr}_{i,a,t} + \beta_4 Dem^{incr}_{i,a,t} + \varepsilon_{i,a,t}\end{aligned} \tag{D.1}$$

Individual bank-area growth rates can be written as

$$\begin{aligned}\Delta L^{\%}_{i,a,t} = \Delta L^{\%,0}_{i,a,t} + \left(\Delta L^{\%,1,tight}_{i,a,t} - \Delta L^{\%,0,tight}_{i,a,t}\right) Sup^{tight}_{i,a,t} \\ + \left(\Delta L^{\%,1,ease}_{i,a,t} - \Delta L^{\%,0,ease}_{i,a,t}\right) Sup^{ease}_{i,a,t}.\end{aligned} \tag{D.2}$$

It follows that the growth rate of loans by bank i in area a at time t if bank i did not ease or tighten its supply, irrespective of whether it eased or tightened its supply, is given by

$$\begin{aligned}\Delta L_{i,a,t}^{\%,0} = \Delta L_{i,a,t}^{\%} - \underbrace{\left(\Delta L_{i,a,t}^{\%,1,tight} - \Delta L_{i,a,t}^{\%,0,tight}\right)}_{\beta_1} Sup_{i,a,t}^{tight} \\ - \underbrace{\left(\Delta L_{i,a,t}^{\%,1,ease} - \Delta L_{i,a,t}^{\%,0,ease}\right)}_{\beta_2} Sup_{i,a,t}^{ease}.\end{aligned} \tag{D.3}$$

Averaging Equation (D.3) out of the entire *population* gives the following equation:

$$\begin{aligned}\frac{\sum_i \sum_a^N \Delta L_{i,a,t}^{\%,0}}{N} = \overline{\Delta L}_t^{\%,0} = \frac{\sum_i \sum_a^N \Delta L_{i,a,t}^{\%}}{N} \\ - \beta_1 \frac{\sum_i \sum_a^N Sup_{i,a,t}^{tight}}{N} - \beta_2 \frac{\sum_i \sum_a^N Sup_{i,a,t}^{ease}}{N}.\end{aligned} \tag{D.4}$$

$\frac{\sum_i \sum_a^N Sup_{i,a,t}^{tight}}{N}$ is the *population* share of bank areas that tighten their supply. $\frac{\sum_i \sum_a^N Sup_{i,a,t}^{ease}}{N}$ is the *population* share of bank areas that ease their supply. The *sample* counterpart of (D.4) is

$$\widehat{\overline{\Delta L}}_t^{\%,0} = \frac{\sum_i \sum_a^N \Delta L_{i,a,t}^{\%}}{N} - \hat{\beta}_1 \frac{\sum_i \sum_a^n Sup_{i,a,t}^{tight}}{n} - \hat{\beta}_2 \frac{\sum_i \sum_a^n Sup_{i,a,t}^{ease}}{n}. \tag{D.5}$$

The first term on the right-hand side of the last equation is known. $\hat{\beta}_1$ and $\hat{\beta}_2$ are the estimates of β_1 and β_2 from the benchmark model. The last two terms are assumed to be a non-biased estimate of

$$\begin{aligned}\frac{\sum_i \sum_a^N Sup_{i,a,t}^{tight/ease}}{N} = \left(\frac{n}{N} \frac{\sum_i \sum_a^n Sup_{i,a,t}^{tight/ease}}{n}\right) \\ + \left(\frac{N-n}{N} \frac{\sum_i \sum_{a\ n+1}^N Sup_{i,a,t}^{tight/ease}}{N-n}\right).\end{aligned} \tag{D.6}$$

In relation to $\hat{\beta}_2 = 0$, the estimated *individual average effect* of the *actual change* in supply is equivalent to the estimated *average effect* of the *actual tightening* in supply (given that $\hat{\beta}_2 = 0$, only the tight side of supply is relevant to the calculation):

$$\underbrace{\hat{\beta}_1}_{\substack{\text{how}\\\text{much}}} \underbrace{\frac{1}{n} \sum_i \sum_a^n Sup_{i,a,t}^{tight}}_{\substack{\text{how}\\\text{many}}}. \tag{D.7}$$

Nevertheless, Equation (D.7) is the average contribution and not the *overall* supply contribution. Simple algebra shows that the *overall population* growth rate of loans is given by

$$\begin{aligned}\Delta L_t^{\%} &= 100 \frac{\Delta L_t}{L_{t-1}} = 100 \frac{\sum_i \sum_a^N \Delta L_{i,a,t}}{\sum_i \sum_a^N L_{i,a,t-1}} \\ &= 100 \sum_i \sum_a^N \frac{\Delta L_{i,a,t}}{L_{i,a,t-1}} \frac{L_{i,a,t-1}}{\sum_i \sum_a^N L_{i,a,t-1}} \\ &= \sum_i \sum_a^N \Delta L_{i,a,t}^{\%} \frac{L_{i,a,t-1}}{\sum_i \sum_a^N L_{i,a,t-1}}.\end{aligned} \tag{D.8}$$

By using the previous result, I can get Equation (D.10) and Equation (D.11):

$$\begin{aligned}\Delta L_t^{\%,0} &= 100 \frac{\Delta L_t^0}{L_{t-1}} = 100 \frac{\sum_i \sum_a^N \Delta L_{i,a,t}^0}{\sum_i \sum_a^N L_{i,a,t-1}} \\ &= 100 \sum_i \sum_a^N \frac{\Delta L_{i,a,t}^0}{L_{i,a,t-1}} \frac{L_{i,a,t-1}}{\sum_i \sum_a^N L_{i,a,t-1}} \\ &= \sum_i \sum_a^N \Bigg[\Delta L_{i,a,t}^{\%} - \underbrace{\left(\Delta L_{i,a,t}^{\%,1,tight} - \Delta L_{i,a,t}^{\%,0,tight} \right)}_{\beta_1} Sup_{i,a,t}^{tight} \\ &\quad - \underbrace{\left(\Delta L_{i,a,t}^{\%,1,ease} - \Delta L_{i,a,t}^{\%,0,ease} \right)}_{\beta_2} Sup_{i,a,t}^{ease} \Bigg] \frac{S_{i,a,t-1}}{\sum_i \sum_a^N L_{i,a,t-1}}\end{aligned} \tag{D.9}$$

$$\Delta L_t^{\%,0} = \Delta L_t^{\%} - \beta_1 \sum_i \sum_a^N Sup_{i,a,t}^{tight} \frac{L_{i,a,t-1}}{\sum_i \sum_a^N L_{i,a,t-1}} - \beta_2 \sum_i \sum_a^N Sup_{i,a,t}^{ease} \frac{L_{i,a,t-1}}{\sum_i \sum_a^N L_{i,a,t-1}} \tag{D.10}$$

$$\widehat{\Delta L}_t^{\%,0} = \Delta L_t^{\%} - \hat{\beta}_1 \sum_i \sum_a^n Sup_{i,a,t}^{tight} \frac{L_{i,a,t-1}}{\sum_i \sum_a^n L_{i,a,t-1}} - \hat{\beta}_2 \sum_i \sum_a^n Sup_{i,a,t}^{ease} \frac{L_{i,a,t-1}}{\sum_i \sum_a^n L_{i,a,t-1}}. \tag{D.11}$$

$\Delta L_t^{\%}$ is known, $\hat{\beta}_1$ and $\hat{\beta}_2$ are the estimates of β_1 and β_2 from the benchmark model, and the no-bias assumption works for

$$\sum_i \sum_a^N Sup_{(i,a),t}^{tight/ease} \frac{L_{i,a,t-1}}{\sum_i \sum_a^N L_{i,a,t-1}} = \left(\frac{\sum_i \sum_a^n L_{i,a,t-1}}{\sum_i \sum_a^N L_{i,a,t-1}} \sum_i \sum_a^n Sup_{i,a,t}^{tight/ease} \frac{L_{i,a,t-1}}{\sum_i \sum_a^n L_{i,a,t-1}} \right) + \left(\frac{\sum_i \sum_{a\ n+1}^N L_{i,a,t-1}}{\sum_i \sum_a^N L_{i,a,t-1}} \sum_i \sum_{a\ n+1}^N Sup_{i,a,t}^{tight/ease} \frac{L_{i,a,t-1}}{\sum_i \sum_{a\ n+1}^N L_{i,a,t-1}} \right). \tag{D.12}$$

In relation to $\hat{\beta}_2 = 0$, the estimated *overall contribution* of the *actual change* in supply is equivalent to the estimated *overall contribution* of the *actual tightening* in supply (given that $\hat{\beta}_2 = 0$, only the tight side of supply is relevant to the calculation):

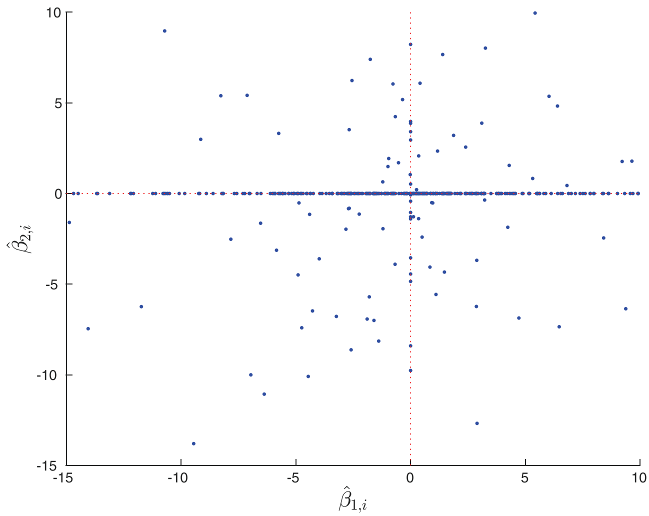
$$\underbrace{\hat{\beta}_1}_{\substack{\text{how}\\\text{much}}} \underbrace{Sup_{i,a,t}^{tight}}_{\substack{\text{how}\\\text{many}}} \underbrace{\frac{L_{i,a,t-1}}{\sum_i \sum_a^n L_{i,a,t-1}}}_{\substack{\text{individual impact}\\\text{factor}}}. \tag{D.13}$$

An inspection of Equations (D.6) and (D.12) and of Expressions (D.7) and (D.13) yields some interesting insights. First, the *individual average effect* potentially suffers from a sample bias more than the *overall contribution*. Usually, but this is not the case in the RBLS, a great number of small banks are not sampled. Second, Equation (D.13) suggests a method for performing the calculation easily by combining three elements: the market loan growth rate, $\hat{\beta}_1$ and a simple loan-lagged-weighted average of the tightening indicators.[48] Allowing for a heterogeneous $\hat{\beta}_1$, Expression (D.13) reads as follows (g indices groups):

$$\sum_g \left[\hat{\beta}_1^g \sum_{i \in g} \sum_{a \in g}^{n_g} Sup_{i,a,t}^{tight} \frac{L_{i,a,t-1}}{\sum_i \sum_a^n L_{i,a,t-1}} \right]. \tag{D.14}$$

Appendix E. Heterogeneity

Figure E.1. Individual Estimates (supply side)

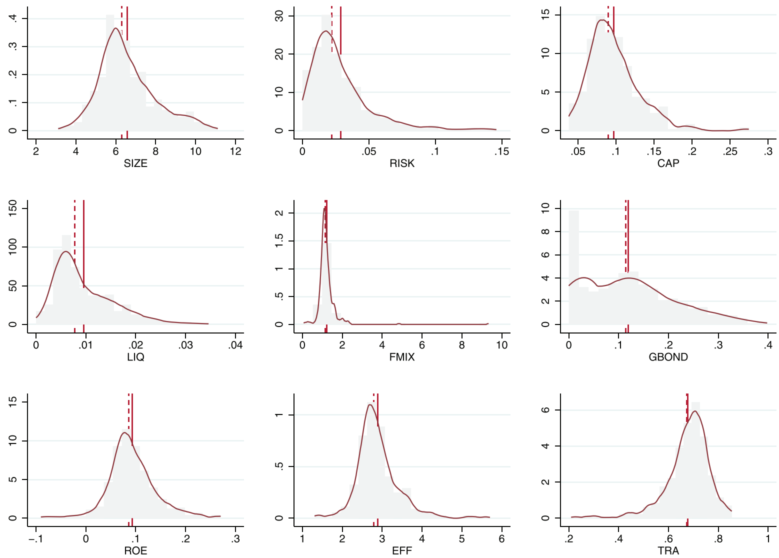


Note: X-axis: tightening; y-axis: easing. Seventy-four estimates are out of range. The estimates are the outcome of a regression with supply, demand, semester, and year dummies over the available time series for each bank area. Forty-seven percent of tight coefficients have a strictly negative sign. Thirteen percent of easing coefficients have a strictly positive sign. Unbalanced panel of 420 banks.

[48]When $\hat{\beta}_2 \neq 0$, the easing indicator also needs to be considered.

Appendix F. Balance Sheet Indicators

Figure F.1. Distributions



Note: Indicators are from a simple 2005–06 average. For two banks some balance sheet data refer to 2007. Values above the 1st–99th percentile are not displayed. Median: dashed vertical line (for TRA the 40th percentile replaces the median). Mean: solid vertical line. SIZE: logarithm of total assets. RISK: bad debts to total loans. CAP: capital and reserves to total assets. LIQ: cash and ECB deposits to total assets. FMIX: deposits and bank bonds over total loans. GBOND: government bonds over total assets. ROE: net profit over capital and reserves. EFF: gross income over personnel costs. TRA: net interest income over gross income. Unbalanced panel of 413 banks.

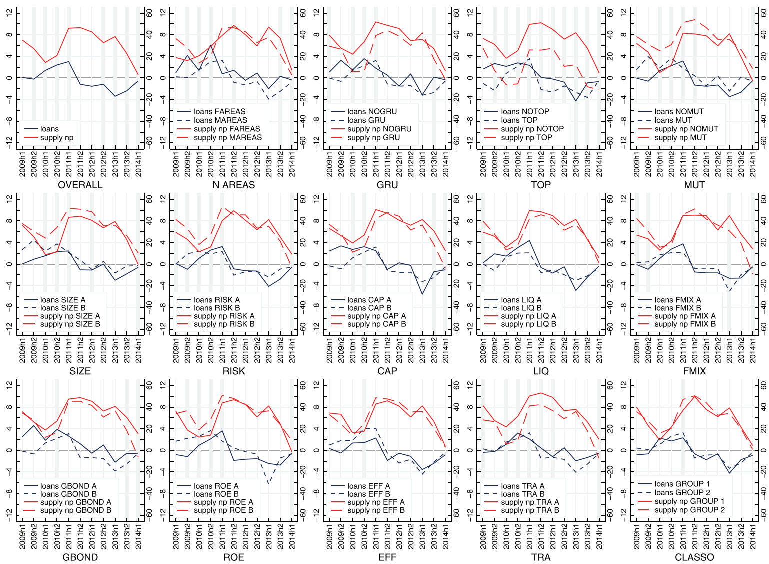
Table F.1. Correlations

	SIZE	RISK	CAP	LIQ	FMIX	GBOND	ROE	EFF	TRA
SIZE	1								
RISK	–0.0315	1							
CAP	–0.3075*	–0.1283*	1						
LIQ	0.3123*	0.1429*	–0.0751	1					
FMIX	–0.2252*	0.1380*	0.0557	0.0848	1				
GBOND	–0.5399*	0.0362	0.2252*	–0.1622*	0.3947*	1			
ROE	0.1380*	–0.1671*	–0.2591*	–0.1332*	–0.1283*	–0.1428*	1		
EFF	0.2252*	–0.0315	–0.0170	–0.0944	–0.1768*	–0.1332*	0.2930*	1	
TRA	–0.4069*	–0.0296	0.2647*	–0.1995*	0.1304*	0.3615*	–0.1106	–0.0711	1

Note: Listwise correlations. $*p < 0.01$. The table shows the correlations between dummies equal to 1 if the variable is above the median (for TRA the 40th percentile replaces the median). The results are confirmed by using the indicators in their original (continuous) form. 413 banks.

Appendix G. Data by Groups

Figure G.1. Growth Rates of Loans and Supply Net Percentages



Note: Growth rates of loans to non-financial corporations (left-hand scale, percentage points; half-yearly growth rates adjusted—securitizations, reclassifications, and other variations that are not a result of ordinary transactions—at the bank-area level) and RBLS net percentages (right-hand scale, percentage points) for non-financial corporations. Thick vertical lines indicate statistical significance (at least 10 percent) of the difference in the net percentages (two-sided Welch test). First part: FAREAS: banks operating in one or two areas. MAREAS: banks operating in three or four areas. NOGRU: banks not in a banking group. GRU: banks in a banking group. NOTOP: banks not in one of the top five banking groups (according to funds intermediated). TOP: banks in one of the top five banking groups (according to funds intermediated). NOMUT: non-mutual banks. MUT: mutual banks (mutual banks are small non-profit community banks). Unbalanced panel of 420 banks. Second part: data by above (A) and below (B) median balance sheet indicators of the banks (for TRA the 40th percentile replaces the median). Balance sheet classification is performed according to the 2005–06 average. For two banks, some balance sheet data refer to 2007. The outcome is robust to using banking-group-level data. SIZE: logarithm of total assets. RISK: bad debts to total loans. CAP: capital and reserves to total assets. LIQ: cash and ECB deposits to total assets. FMIX: deposits and bank bonds over total loans. GBOND: government bonds over total assets. ROE: net profit over capital and reserves. EFF: gross income over personnel costs. TRA: net interest income over gross income. Unbalanced panel of 413 banks. Third part: data by C-Lasso groups. Balanced panel of 301 banks.

Appendix H. C-Lasso: Technical Details

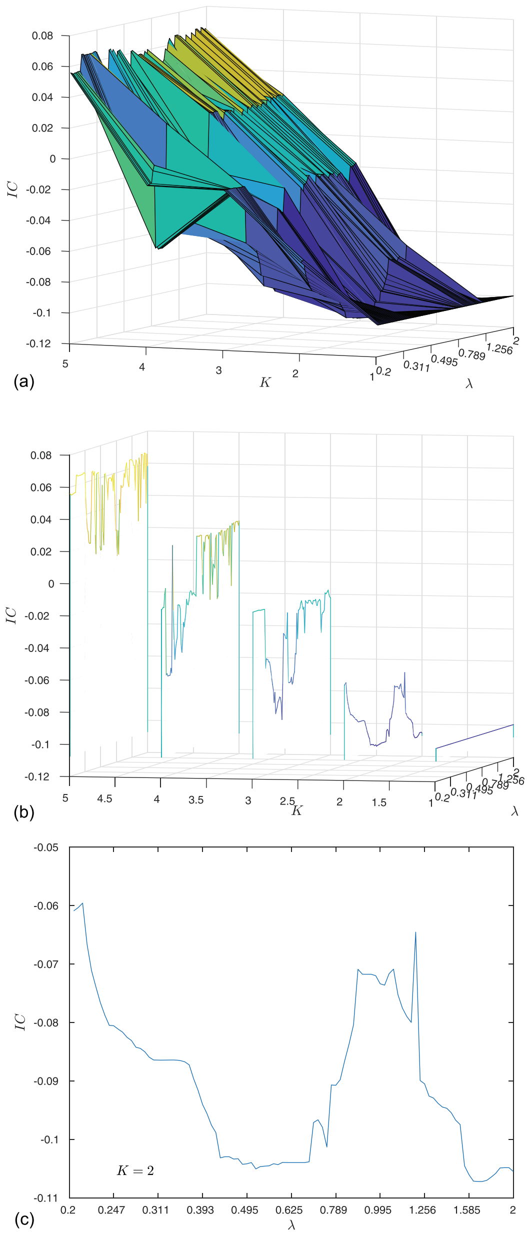
Data have been treated by first balancing the panel.[49] Second, each variable is transformed into its residuals after a regression on a full set of bank-area, area-year, and semester dummies. Third, all variables are standardized at the bank-area level: the C-Lasso is scale variant and this is the procedure suggested by Su, Shi, and Phillips (2016). Here C-Lasso and post C-Lasso are sign restricted.[50] The information criterion (IC) of Su, Shi, and Phillips (2016) finds two homogeneous groups.[51] Once groups are identified, I conveniently report post–C-Lasso estimates for the non-standardized variables. Figure H.1 shows IC details.

[49]The unbalanced panel is made up of 420 banks and 621 bank-area observations; the balanced one is made up of 301 banks and 369 bank-area observations.

[50]$\beta_1, \beta_3 \leq 0$ (tight in supply and decrease in demand) and $\beta_2, \beta_4 \geq 0$ (easing in supply and increase in demand). The C-Lasso works on both supply and demand coefficients.

[51]The tuning parameter ranges from 0.2 to 2 with a grid of 100 points. The number of groups ranges from one to five. The starting values of the algorithm are given by the slope parameters of individual bank-area regressions. MATLAB codes are available upon request.

Figure H.1. Information Criterion (IC) of Su, Shi, and Phillips (2016)



Note: The maximum value of K (groups) is 5. The tuning parameter ranges from 0.2 to 2 with a grid of 100 points. The optimal values are $K = 2$ and $= 1.6604$.

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