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11 The Case for a Credit Registry

Atif Mian

11.1 Introduction

The banking sector is often blamed for exposing the economy to systemically important risks through either excessive credit creation and asset bubbles during episodes of credit boom, or excessive cut back in credit during slumps. The basic reasoning behind such arguments is that credit supply matters. For example, a relaxation in lending standards may lead to excessive credit creation during booms and large losses to capital may generate a deleveraging cycle that wipes out good credit during busts.

The concern that malfunctions in the credit supply process may generate unnecessary crises leads to calls for large scale policy intervention in credit markets. For example, central banks are advised to "lean against the wind" if credit is expanding due to lax lending practices. On the other hand, central banks and governments are urged to inject liquidity and capital in the banking system if credit is being cut due to a deleveraging process.

This chapter seeks to answer the following question:

> What tools does a regulator or policymaker have at her disposal to judge whether changes in bank credit are driven by supply-side factors?[1]

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1. My focus here is on commercial lending to firms. A related question corresponding to consumer financing is discussed by Amir Sufi in "Detecting Bad Leverage" (chapter 14, this volume).

The question is important because if changes in bank credit were driven by genuine demand-side factors such as productivity shocks or shocks to expectations, then policy intervention based on the premise that the fault lies on the credit supply side can be counterproductive. Moreover, even if supply-side factors influence bank credit, these factors may not be too relevant for the economy if there are sufficient new and alternative sources of financing to pick up any slack created by misperforming banks.

I outline a methodology that can help policymakers better understand the extent to which supply-side factors generate aggregate fluctuations in credit. The methodology is based on the regulator having access to a timely and comprehensive *credit registry* that contains information on every business loan given out by the banking sector. While such credit registry data are available in many countries around the world, the United States does not currently have a comparable system. I discuss the design issues related to the building up a credit registry database in section 11.2. Section 11.3 outlines the methodology that can be applied to credit registry data to isolate the role of supply-side factors and section 11.4 provides real world examples. Section 11.5 concludes with a discussion of some of the limitations of the proposed methodology.

11.2 Credit Registry Design

I begin with a brief description of the design of credit registries (see World Bank [2011] for more details). There are four basic steps in the design of a credit registry system: data collection, data validation, data dissemination, and data usage.

Data collection. Credit registry data are collected from every commercial borrower in the banking system. The data contain identification information on borrower and lender, and may include details such as name, location, industry, and ownership information. Information on location, industry, and ownership is particularly useful for testing if credit is concentrated in certain regions, industries, or groups of companies and whether such trends have strengthened over time. A typical credit registry records both positive and negative credit information. Positive credit information includes total amount of credit issued, credit outstanding, maturity, and collateral value (if any). Negative credit information includes default rate (broken by thirty-day, sixty-day, etc.), recovery in case of default, and any legal actions against the borrower in the past. In certain countries there may be a sunset provision on negative information such that negative information is automatically deleted from the record after a predetermined number of years. It is common for credit registry data to be updated on a monthly basis. With the advancements in information technology, collecting credit registry data at a monthly frequency is not too cumbersome.

Data validation. An important step after data collection is its validation to minimize errors. Automated routines can be set up to check if the data are coded appropriately and whether individual data items add up to the consolidated version. Any significant discrepancy found in the validation stage can be sent back to the data collection stage for further verification. Random audits of loan-level data are also useful in strengthening data quality and incentivizing data collectors to monitor the process appropriately. Such audits not only help keep the data quality high but also improve transparency and reliability of the banking sector financial data.

Data dissemination. Every credit registry data must have appropriately designed rules on how data will be disseminated and who can get access to the data. There is a fundamental tension between maintaining proprietorship of data and making data accessible to a wider audience. Banks that rely on "relationship banking" may want to keep their portfolio confidential to maximize leverage and rents in their relationship. Doing so may—in theory—also be optimal ex ante to give incentives to banks to spend effort in adding first-time borrowers to the banking sector. However, such benefits of data proprietorship must be weighed against the broader benefits of data sharing. These include enabling banks to get a real time sense of the overall exposure of their clients (and related parties) with other banks and allowing regulators/researchers quick access to data for macroprudential purposes (as explained in the following sections).

Putting all this together, while it is important to create and share credit registry data, it is equally important to outline strict guidelines on who can access the data and how. It is imperative that everyone contributing to the credit registry data must have full confidence that the data will only be used for legitimate purposes.

Data usage. Once a credit registry data is put in place, an obvious use of the data is to help regulators and the banking sector use the data for prudential and risk-management purposes. The rest of this chapter explains how the data can also be combined with more scientific empirical methodologies to better identify the fundamental drivers of credit boom and bust. The accumulated knowledge can then help policymakers make more informed choices.

11.3 Methodology

The methodology outlined here was introduced by Khwaja and Mian (2008) and augmented by Jiménez et al. (2011). The basic purpose of the methodology is to test specific hypotheses about the role of supply-side factors in generating observed changes in bank credit. The methodology offers two advantages from an econometric standpoint. First, it provides an unbiased estimate of the supply-driven "bank lending channel" effect. Second, it takes into account general equilibrium adjustments made at the borrower level in reaction to the bank lending channel effect and provides a bias-corrected net effect of the bank lending channel at the borrower level. We briefly illustrate the methodology below.

Consider an economy with banks and firms indexed by i and j, respectively. Firm j borrows from n_j banks at time t, and assume that it borrows the same amount from each of the n_j banks. The economy experiences two shocks at t: a firm-specific credit demand shock η_j and a bank-specific credit supply shock δ_i. The variable η_j reflects changes in the firm's demand for credit driven by productivity or customer demand shocks. Variable δ_i reflects changes in the bank's funding situation, such as a run on short-term liabilities (a negative shock), or new opportunities to access wholesale financing (a positive shock.)

Let y_{ij} denote the log change in credit from bank i to firm j. Then the basic credit channel equation in the face of credit supply and demand shocks can be written as:

$$y_{ij} = \alpha + \beta * \delta_i + \eta_j + \varepsilon_{ij}. \tag{1}$$

Equation (1) assumes that the change in bank credit from bank i to firm j is determined by an economy-wide secular trend α, credit supply and credit demand shocks, and an idiosyncratic shock ε_{ij}. While equation (1) is reduced form in nature, it can be derived as an equilibrium condition by explicitly modeling credit supply and demand schedules.

In a frictionless world (as in the Modigliani-Miller theorem), bank lending is independent of credit supply conditions and only depends on "fundamental" credit demand factors. Financial intermediaries in such scenarios have no impact on the economy and, hence, there is no bank transmission channel, that is, $\beta = 0$ in equation (1). The presence of financing frictions, however, may force banks to pass on their credit supply shocks δ_i to borrowing firms, making $\beta > 0$

Variable β is often referred to as the "bank lending channel," and is the key supply-side parameter of interest. Variable β can be estimated from equation (1) using ordinary least squares (OLS), giving us $\hat{\beta}_{OLS} = \beta + [Cov(\delta_i, \eta_j) / Var(\delta_i)]$. The expression implies that as long as credit supply and demand shocks are significantly correlated, $\hat{\beta}_{OLS}$ in equation (1) would be a biased estimate of the true β. For example, if banks receiving a positive liquidity shock are more likely to lend to firms that simultaneously receive a positive credit demand boost, then β would be biased upward. Khwaja and Mian (2008) resolve this issue by focusing on firms with $n_j \geq 2$, and absorbing out η_j through firm fixed effects. The estimated coefficient $\hat{\beta}_{FE}$ then provides an unbiased estimate of β.

However, $\hat{\beta}_{FE}$ does not give us a complete picture of the net effect of bank lending channel on the economy. In particular, individual firms affected by the local lending channel due to a positive β in equation (1) may seek funding from new banking relationships to compensate for any loss of credit. Jimenez et al. (2011) show that an unbiased estimate of the *net* (or aggregate) effect of supply-side banking shocks on borrower j can be estimated using the equation:

$$(2) \qquad \bar{y}_j = \bar{\alpha} + \bar{\beta} * \bar{\delta}_j + \eta_j + \bar{\varepsilon}_j,$$

where $\bar{y}_j$ denotes the log change in credit for firm j across *all* banks.[2] It is *not* a simple average of y_{ij} from equation (1), since a firm can start borrowing from new banks as well. Variable $\bar{\delta}_j$ denotes the *average* banking sector shock experienced by firm j at time t, that is, $\bar{\delta}_j = \sum_{i \in N_j} \delta_i / n_j$, where N_j represents the set of banks lending to firm j at time t. Variable $\bar{\varepsilon}_j$ is an idiosyncratic error term. The same credit demand shock η_j appears in both equations (1) and (2) under the assumption that the shock equally affects a firm's borrowing from all banks. The aggregate impact of credit supply channel is captured by the coefficient $\bar{\beta}$. If there is no adjustment at firm level in the face of bank-specific credit channel shocks, then $\bar{\beta} = \beta$.

How does one estimate $\bar{\beta}$? An OLS estimate of equation (2) yields $\hat{\bar{\beta}}_{OLS} = \bar{\beta} + [Cov(\delta_i, \eta_i) / Var(\bar{\delta}_j)]$.[3] While the variance of $\bar{\delta}_j$ can be estimated in data, the covariance term between credit demand and credit supply shocks is unobservable to the econometrician. However, a unique advantage of the preceding fixed-effects estimator at loan level is that it allows us to back out the covariance term. Since $\hat{\beta}_{FE}$ is an unbiased estimate of β, we can write $Cov(\delta_i, \eta_j) = (\hat{\beta}_{OLS} - \hat{\beta}_{FE}) * Var(\delta_i)$, where variance of bank credit supply shocks δ_i can be estimated directly from data. Thus the aggregate lending channel effect, $\bar{\beta}$, can be estimated as:

$$(3) \qquad \hat{\bar{\beta}} = \hat{\bar{\beta}}_{OLS} - \left(\hat{\beta}_{OLS} - \hat{\beta}_{FE}\right) * \frac{Var(\delta_i)}{Var(\bar{\delta}_j)}.$$

The second term on the right-hand side of equation (3) is the adjustment term that corrects for any bias in the OLS estimate of equation (2). The adjustment term corrects for the otherwise unobserved covariance between credit supply and demand shocks. The extra variance term in the denominator corrects for the fact that the variance of bank shocks averaged at the firm level may be different from the variance of bank shocks overall.

A key advantage of the proposed methodology is that it can be implemented in real time. In particular, for any given bank shock δ_i that is suspected of generating a transmission channel, run OLS and fixed effects (FE) versions of equation (1) to estimate $\hat{\beta}_{OLS}$ and $\hat{\beta}_{FE}$ respectively. Then estimate firm-level equation (2) using OLS to generate $\hat{\bar{\beta}}_{OLS}$. Finally, plug these three coefficients in equation (3) to estimate the unbiased impact of credit supply channel at the firm level.

A second advantage of the proposed procedure is that it relies on credit registry data, which exists in most countries of the world with banking

2. Depending on data availability, it could include nonbank sources of credit as well.
3. This follows from the observation that $Cov(\bar{\delta}_j, \eta_j) = Cov(\sum_{i \in N_j}(\delta_i / n_i), \eta_j) = Cov(\delta_i, \eta_j)$.

supervision departments. We next provide three examples of the use of this methodology from Pakistan, Spain, and the United States.

11.4 Examples

11.4.1 Nuclear Tests and Dollar Deposit Run on Banks in Pakistan

The unexpected nuclear tests by Pakistan in May 1998 imposed stiff sanctions on the country that led to a serious balance of payment crisis. Consequently, the government defaulted on its obligation to pay back dollars that it had borrowed through the banking sector's "dollar deposit scheme." The default on dollar obligations led to a serious run by depositors on the banking sector. However the run was not uniform across banks, but concentrated on banks that were more reliant on dollar deposits as a funding source.[4]

Khwaja and Mian (2008) evaluate the credit supply consequences of the run on bank deposits. We estimate equation (1) with borrower fixed effects separately for each quarter t. Variable y_{ij} is defined as log change in loan from bank i to firm j. The change is computed from the quarter prior to the nuclear tests until quarter t. Variable δ_i is defined as the log change in deposits for bank i in the aftermath of the nuclear tests.

The set of estimated coefficients $\hat{\beta}_{FE,t}$ (one for each t) trace out the supply-side impact of the run on deposits. Each coefficient $\hat{\beta}_{FE,t}$ is computed using the within-firm difference in loan growth from banks with (relatively) high deposit growth versus banks with low deposit growth. Figure 11.1 plots this difference after classifying above and below median deposit growth as "positive" and "negative" liquidity shocks respectively.

There is no sign of a credit supply effect until the nuclear shock hits. Following the nuclear tests, we see a strong credit supply effect from the run on deposits. While there is a strong credit supply shock at the loan level, Khwaja and Mian (2008) show that this effect is completely neutralized by large firms (top 30 percent of firms by size) as they are able to borrow from new sources of funding. Thus the credit supply shock ends up affecting only smaller firms. Such an analysis can help policymakers understand the magnitude of the credit supply shock, and isolate the set of firms most in need of additional credit support.

11.4.2 Real Estate Securitization and Bank Credit in Spain

Jiménez et al. (2011) apply the aforementioned methodology to the case of Spain and test whether the boom in real estate securitization during the

4. Banks could not hold these dollar deposits themselves. They turned over the dollar deposits to the central bank in exchange for equivalent rupees under the promise that the central bank would return dollars on demand from the depositor.

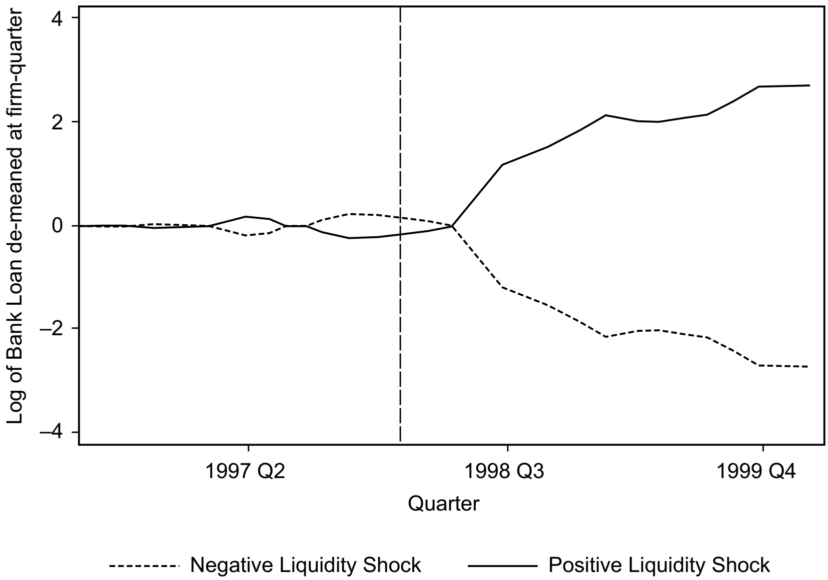

Fig. 11.1 Loan-level credit channel effect for Pakistan

Notes: The figure illustrates the credit supply effect due to the run on deposits in the aftermath of the May 1998 nuclear tests by Pakistan (dashed vertical line). It plots the change in credit within the same firm borrowing from two different types of banks—one that experiences a positive (above-median) growth in deposits and one that experiences negative (below-median) growth in deposits in the aftermath of the nuclear tests.

2000s enabled banks with large real estate assets to expand credit supply by securitizing their real estate portfolio. They estimate equation (1) with borrower fixed effects separately for each quarter t. Variable y_{ij} is defined as log change in loan from bank i to firm j. The change is computed from 2004Q4 until quarter t. Variable δ_i is defined as the ex ante (year 2000) variation in real estate holdings for bank i. Real estate exposure proxies for the capacity of banks to securitize assets during the securitization boom. The analysis utilizes a comprehensive quarterly loan level credit registry data from the Bank of Spain that covers a period from 1999Q4 to 2009Q4.

Figure 11.2 plots the firm fixed-effect estimate of the credit supply effect of real estate exposure, $\hat{\beta}_{FE,t}$. Starting in 2004 (when securitization in Spain shoots up), there is a strong positive credit supply effect for banks with real estate exposure due to improved access to wholesale financing. The positive credit supply effect turns negative in 2008, however, as the global securitization market shuts down.

Jiménez et al. (2011) show that despite a significant loan-level credit supply effect, the net (aggregate) impact of securitization at the borrower level is muted due to a "crowding out" effect. Nonetheless, there is a sig-

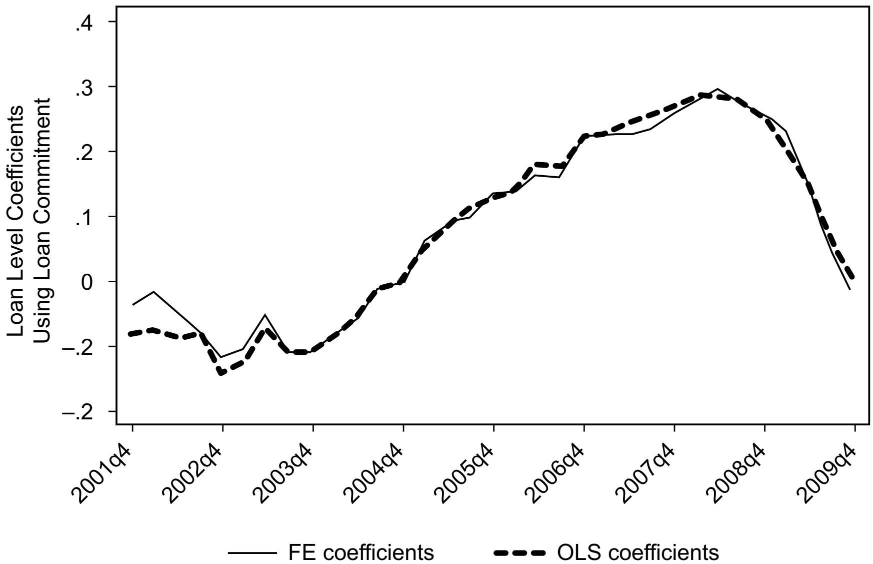

Fig. 11.2 Loan-level credit channel coefficients for Spain by quarter

Notes: The figure plots the coefficient estimates for β^t for the following specification for each quarter t: $y_{ijt} - y_{ij,04q4} = \alpha^t + \beta^t * \boldsymbol{REexposure}_{i,2000} + \eta_{jt} + \varepsilon_{ijt}$, where y is the natural logarithm of loan commitment amount for firm j from bank i. $\boldsymbol{REexposure}_{i,2000}$ is the share of loan portfolio exposed to real estate for bank i in 2000. The OLS coefficient estimates do not include the firm fixed effects term, η_{jt}.

nificant aggregate impact of the expansion in credit supply on the price of credit. Securitization also leads to a reduction in loan collateralization rates and lengthens the maturity of loans.

11.4.3 US Financial Crisis and Bank Credit Lines

Some observers argue that a reduction in the supply of credit to corporations was an important factor in precipitating the economic downturn during 2007 and 2008. Ivashina and Scharfstein (2010) show that corporations drew down on their lines of credit significantly during this period, and especially more so from banks experiencing larger losses and thus under greater threat of going bankrupt. One interpretation of this evidence is that there was a “run” by corporations on weak banks under the fear that future credit supply may be choked off.

However, in a recent paper using loan-level data from the Fed’s SNC program, Mian and Santos (2011) show that the increase in drawn lines of credit is not unique to the 2007 to 2009 crisis. The same pattern is seen in each of the previous two recessions of 1990 to 1991 and 2001 as well, and there was no banking crisis in 2001. Thus, an alternative demand-based explanation for the increase in draw-down ratio is that as the economy slows, firms draw down as much as they can before their credit worthiness deteriorates.

We can use the above-mentioned methodology to test if the corporate run on undrawn lines of credit was driven by credit supply shock. Using loan-level data on syndicate loans from the Fed, we estimate equation (1), with y_{ij} defined as change in draw down percentage of a syndicate loan from lead bank i to firm j. Variable δ_i captures the exposure of a lead bank to the crisis, which we proxy using the bank's ultimate charge-offs to assets. We also add the initial level of draw-down percentage on the right-hand side since the change in draw down is mechanically related to the initial draw-down percentage.

While simple OLS estimation of equation (1) over 2006 to 2007 and 2007 to 2008 shows that banks with larger ultimate losses experience larger increase in draw-down percentage, this result is entirely driven by less creditworthy firms more likely to borrow from banks with greater exposure to the crisis. The unbiased borrower fixed-effect estimate $\hat{\beta}_{FE}$ is no longer positive with reasonably small standard errors. Thus the correlation between bank losses and increase in borrower draw-down ratio is driven by the endogenous matching of firms with low credit worthiness to banks that end up experiencing large losses.

11.5 Concluding Discussion

Most concerns about systemic risk relating to the banking industry are based on the premise that bank credit supply may get out of whack with economic fundamentals. This chapter outlined a methodology that can be used to test specific hypotheses about the extent to which changes in credit are driven by supply-side factors. The methodology uses loan-level credit registry data that are increasingly available in many countries. However, surprisingly, the United States lags behind in the availability of detailed loan-level data. Ideally, one would like to have loan-level data that covers the entire banking sector, and follows not just loan quantities but also price terms such as interest rate, maturity, collateralization rate, and basic covenants.

While I discussed three examples relating to my own work, other scholars have also used the methodology highlighted here in conjunction with credit registry data to isolate credit supply effects. These include Cetorelli and Goldberg (forthcoming) on international transmission of credit supply shocks during 2007 to 2008, Lin and Paravisini (2010) on the credit supply effect of bank reputation in the United States, Paravisini (2008) on credit supply effects in Argentina, Jiménez et al. (2010, forthcoming) on credit supply effects of monetary policy in Spain, and Schnabl (forthcoming) on the international transmission of credit supply shocks in Peru.

I end with some caveats regarding the use of this methodology in practice. First, the use of credit registry data is feasible at a monthly or quarterly frequency only. Thus, analysis of the sort discussed in this chapter is more suitable for low-frequency analysis.

Second, the methodology is based on a cross-sectional comparison of changes in loans over time, and may be viewed as a specific version of the difference-in-differences approach. As such, the methodology is useful to the extent that there are legitimate reasons to believe that the impact of credit supply is not uniform across all banks.

Third, the methodology by design limits the analysis to borrowers with multiple banking relationships. There is thus a concern that single-relationship borrowers that may be most adversely impacted by credit supply shocks are left out. However, more than three quarters of bank lending often goes to borrowers with multiple relationships. Moreover, variation within multiple-relationship firms can also be used to test if credit supply shocks affect smaller firms differentially.

References

Cetorelli, Nicola, and Linda S. Goldberg. Forthcoming. "Global Banks and International Shock Transmission: Evidence from the Crisis." *IMF Economic Review*.

Ivashina, V., and D. Scharfstein. 2010. "Bank Lending during the Financial Crises of 2008." *Journal of Financial Economics* 97:319–38.

Jiménez, Gabriel, Atif Mian, José-Luis Peydró, and Jesús Saurina. 2011. "Local versus Aggregate Lending Channels: The Effects of Securitization on Corporate Credit Supply In Spain." Working Paper, Princeton University.

Jiménez, Gabriel, Steven Ongena, José-Luis Peydró, and Jesús Saurina. 2010. "Credit Supply: Identifying Balance-Sheet Channels with Loan Applications and Granted Loans." Discussion Paper 7655. Center for Economic Policy Research.

———. Forthcoming. "Hazardous Times for Monetary Policy: What do Twenty-Three Million Bank Loans Say about the Effects of Monetary Policy on Credit Risk?" *American Economic Review*.

Khwaja, Asim I., and Atif Mian. 2008. "Tracing the Impact of Bank Liquidity Shocks." *American Economic Review* 98 (4): 1413–42.

Lin, Huidan, and Daniel Paravisini. 2010. "What's Bank Reputation Worth? The Effect of Fraud on Financial Contracts and Investment." Working Paper, London School of Economics.

Mian, Atif, and Joao Santos, 2011. "Liquidity Risk, Maturity Management, and the Business Cycle." Working Paper, Princeton University.

Paravisini, Daniel. 2008. "Local Bank Financial Constraints and Firm Access to External Finance." *Journal of Finance* 63 (5): 2161–93.

Schnabl, Philipp. Forthcoming. "The International Transmission of Bank Liquidity Shocks: Evidence from an Emerging Market." *Journal of Finance*.

World Bank. 2011. "General Principles for Credit Reporting." Consultative Report, March. Washington, DC: The World Bank.