

The Effects of Informational Frictions on Credit Reallocation

Olivier Darmouni*

JOB MARKET PAPER

[Latest version]

January 10, 2016

Abstract

This paper studies the role of an informational friction limiting the reallocation of credit after a shock. Lenders have private information about their borrowers, and borrowers left looking for a new lender are adversely selected. Exploiting the financial crisis as a shock to relationships in the U.S. corporate loan market, I provide evidence that lenders use their information to choose which relationships to end when reducing lending. To quantify the effects of this friction on aggregate lending, I model a credit market with three layers of information: (i) all lenders have some information about borrowers, but (ii) each lender has private information about its existing borrowers, and (iii) the econometrician observes neither. I introduce a novel empirical approach that identifies this private information separately from information common to all lenders. At the borrower level, the probability that a firm finds a new lender after a breakup would be 30% higher if there were no private information. At the aggregate level, \$15 billion new loans were not made because of this friction. A naive model ignoring information common to all lenders overestimates the effects of the information gap threefold relative to my estimates. Moreover, interventions supporting weak lenders exacerbate adverse selection and reduce the share of borrowers that are able to reallocate toward new lenders.

Keywords: Informational frictions, Aggregate effects of credit supply shocks, Banking relationships.

*Princeton University. Email: darmouni@princeton.edu. I am indebted to David Sraer, Jakub Kastl, Markus Brunnermeier, Motohiro Yogo, and Valentin Haddad for their continuous support. I would also like to thank Tobias Berg, Saki Bigio, Jan De Loecker, Maryam Farboodi, Martin Hellwig, Adrien Matray, Atif Mian, Justin Murfin, Matthew Plosser, Wei Xiong, Nemanja Antic, Matthieu Gomez, Réka Juhász, John Kim, Stephan Luck, Christian Moser, Pedro Olea, Felix Matthys, Alex Rodnyansky, Paul Schempp, Michael Sockin, Juha Tolvanen, Sharon Traiberman, and Dan Zeltzer for many discussions and comments that improved this paper. Special thanks to Gabriel Chodorow-Reich for his help and support at the early stages of this project.

1 Introduction

The defining feature of a lending relationship between a bank and a borrower is its stickiness: switching lenders is rare and costly.¹ In turn, credit markets are more vulnerable: an idiosyncratic shock forcing a particular bank to cut lending can have *aggregate* effects if affected borrowers cannot easily find a new lender to compensate.² Understanding exactly why relationships are sticky is important, as it can guide the design of institutions or policies to prevent breakdowns in lending markets.

This paper estimates the effects on aggregate lending of a key friction behind relationship stickiness: the *information gap* between a borrower’s existing lender and its potential new lenders. In the course of a relationship, lenders acquire abstract and hard to verify (“soft”) information about their borrowers that is unobservable to other lenders.³ The information gap represents the informational advantage that stems from relationship lending. I develop a novel empirical strategy to quantify the information gap and its effects on lending. Applying this approach to the U.S. corporate loan market, I find that \$15 billion of loans were not made following the financial crisis because of this friction. I also use the model estimates to assess the effectiveness of various credit market policies and institutions.

The channel by which the information gap reduces aggregate lending is by creating adverse selection in the market for borrowers looking for a new relationship. Lenders’ private information gives them the ability to selectively choose which relationships to end when scaling down lending after a shock, leaving their worst borrowers looking for funds elsewhere. Importantly, this adverse selection has aggregate effects only if there is an information gap between lenders. If relationships were ended based on information common to all lenders, this selection would affect the matching

¹See Srinivasan (2014) for a survey of the extensive literature on banking relationships.

²For instance, Chodorow-Reich (2014) shows that bank-specific shocks explain a sizable share of the decline in aggregate firm borrowing and employment after the financial crisis.

³See for example Sharpe (1990), Rajan (1992) or Detragiache et al. (2000). Examples of soft information acquired during a relationship include the quality of management, potential future investment projects, as well as information whose public disclosure would hurt the firm.

of borrowers with lenders but not the share of borrowers receiving a loan.

A key empirical prediction of lenders selectively choosing which relationships to end is that borrowers leaving the most affected lenders are more likely to form a new relationship. Intuitively, the most affected lenders cannot continue lending even to relatively good borrowers. Therefore, a firm's ability to borrow from a new lender after a breakup depends on the size of the shock faced by its previous lender.⁴ Using U.S. syndicated loan market data in the period 2004-2010, I provide evidence consistent with this effect. I exploit the financial crisis that originated in the real estate sector as a shock to relationships in the syndicated loan market and measure a lender's exposure to this shock by the fall in its aggregate lending over the crisis period. I show that conditional on leaving a relationship, a one standard deviation increase in the crisis exposure of a firm's existing lender implies a 15% *increase* in the probability of borrowing from a new lender.

However, this correlation alone cannot identify the information gap, as it is also partly driven by information common to all lenders. In fact, a new lender is more likely to accept borrowers coming from the most affected lender for two reasons: (i) they are inferred to be better along the dimension that is privately observed by their previous lender; and (ii) they are objectively better along the dimension that is commonly observed by all potential new lenders. As the econometrician observes neither of these, it is not possible to separately identify the information gap from the common information component using the reduced form correlation alone. In order to address this challenge, I propose a novel empirical strategy to quantify the information gap and its aggregate effects.⁵ The key idea is to exploit a comparison with the sample of borrowers who renewed their relationships, as relationship renewal reflects how lenders lend to borrowers they have private information about.

⁴This pattern would be difficult to rationalize with alternative frictions, such as fixed costs to set up new relationships or match-specific capital.

⁵Existing approaches have difficulties addressing this challenge. For instance, Gibbons and Katz (1997) find evidence that firms cherry-pick employees when reducing their labor force, but cannot say whether this selection has aggregate effects. Einav et al. (2012) or Einav et al. (2010) model markets where agents are more informed than the econometrician, but all have the same information. Rajan, Seru and Vig (2014) rely on goodness of fit to quantify soft information and cannot distinguish between two types of unobservables.

To this end, I introduce a two-stage discrete choice model of firm borrowing after the crisis. In the first stage, firms try to renew their relationship with their existing lender. Lenders have different abilities to lend after the crisis, depending on their exposure to the aggregate shock. If a borrower fails to receive a new loan from its existing lender, it can turn to new lenders in the second stage. The key ingredient of the model is the existence of three layers of information: (i) all lenders have some information about borrowers, but (ii) each lender has private information about its existing borrowers, and (iii) the econometrician observes neither.

I estimate the first stage by regressing the probability that a firm renews its relationship with its pre-crisis lender on firm and lender characteristics. The identifying assumption is that a lender's crisis exposure is unrelated to the unobservable characteristics of its pre-crisis borrowers.⁶ This first stage corresponds to the lending rule that lenders apply to borrowers they have private information about.⁷ Only borrowers with unobservable quality above a certain cutoff are able to renew their relationship. The information gap is estimated in the second stage, using the subsample of firms that saw their relationship ended in the first stage. I estimate how the probability that a firm finds a new lender depends on the crisis exposure of its previous lender. A larger information gap implies a larger correlation: lending decisions of previous lenders carry more information for new lenders.

Importantly, I use first stage estimates to avoid the bias created by common information. The key idea is that the first stage can be used for *benchmarking* lenders' behavior. Intuitively, if there were no information gap, the lending decision of new lenders in the second stage should match the lending decision rule of informed lenders estimated in the first. More precisely, the counterfactual probability that a particular borrower finds a new lender under the null of common information depends both on its observable and unobservable characteristics. First stage regression estimates

⁶The evidence presented above supports this assumption. If more exposed lenders were matched with worse borrowers, the correlation would go the other way: borrowers coming from the most affected lenders would be less likely to find a new lender.

⁷This lending rule is unlikely to be lender-specific, as lenders are not divided in groups of "informed" vs. "uninformed". In fact, the same lender is informed about some borrowers, but uninformed about others.

directly predict how lending depends on observables. Moreover, the expectation of unobservable quality can be inferred from the likelihood that this borrower reached the second stage, for any parametric assumption on the distribution of borrower unobservables. The difference between this counterfactual borrowing probability and the data represents a residual unexplained by common information.⁸ The information gap is estimated from the correlation between this residual and pre-crisis lender exposure in the cross-section of borrowers.⁹ The maintained assumptions are that the distribution of borrower unobservables and the lending rule (as a function of borrower and lender characteristics) are common across lenders.

The model estimates show that the information gap significantly reduces firms' access to credit. At the borrower level, the probability of forming a new relationship would be 30% higher in the counterfactual in which the information gap is zero. At the aggregate level, an additional \$15 billion of loans would have been made if all lenders had had the same information. Informational frictions thus impose a significant cost on firms by hampering their ability to switch lenders to circumvent credit supply shocks.¹⁰ Moreover, the model's estimates reveal that there is a significant amount of information common to all lenders but unobservable to the econometrician. As a result, ignoring this common information leads to severe bias. A naive model with no common information estimates the information gap and its aggregate effects to be three times larger than in my benchmark model.

I also show that modeling credit reallocation explicitly has new implications for how best to prevent breakdowns in lending markets. There is ample evidence that banking relationships matter, which suggests that policy makers should aim to preserve relationships whenever possible.

⁸As opposed to the literature that identifies informational frictions by comparing firms with different degrees of opacity, this approach relies on comparing how lenders with different information would treat the same firm. The two-step approach bears some resemblance to econometric models in the line of Heckman (1979) but is used to account for differences in information among agents, a feature that is absent from these models.

⁹This cross-sectional approach is valid even though the mean of this residual is likely affected by other frictions, such as fixed costs of establishing a new relationship.

¹⁰This result complements the literature studying interest rates, motivated by the increase in lenders' bargaining power that comes with an information monopoly, including Schonene (2010), Petersen and Rajan (1994), Degryse and Cayseele (2000) and Berger and Udell (1995).

Targeted interventions such the Capital Purchase Program implemented in 2008 are examples of public support directed to the weakest lenders to prevent a breakdown in lending.¹¹ However, a counterfactual exercise shows that these interventions have unintended consequences on credit reallocation that reduce their effectiveness: public support gives lenders a larger opportunity to selectively choose which relationships to end, increasing adverse selection in the market for borrowers looking for a new lender. Such interventions can even reduce lending compared to *laissez-faire*, contrary to what reduced-form models ignoring this equilibrium effect would predict.

I run two additional counterfactual exercises to show how policies and institutions aimed at fostering credit reallocation can boost aggregate lending without directly supporting the weakest lenders. First, I find that improvements in firm transparency can have large effects.¹² I estimate that the information gap is 30% larger for private firms relative to public firms, consistent with the idea that these borrowers are less transparent to outsiders financiers. In a counterfactual in which all firms are as transparent as public firms, aggregate lending would be \$5 billion higher. Second, I study the effect of subsidizing loans made to new borrowers whose existing relationship has ended. As opposed to interventions targeting the weakest lenders, I find that this type of intervention unambiguously increases aggregate lending. It promotes the movement of borrowers by counteracting the stigma associated with leaving a relationship.¹³

This paper relates to the literature estimating the effect of credit supply shocks, including Peek and Rosengren (2000), Khwaja and Mian (2008) and Jimenez, Mian, Peydro and Saurina (2014). In particular, Chodorow-Reich (2014) also studies the U.S. syndicated loan market after the financial crisis. Relative to these papers, I focus on the explicit mechanism by which bank-specific shocks impact firm borrowing. Boualam (2015) offers a theoretical analysis of imperfect

¹¹ The Capital Purchase Program was part of the Troubled Assets Relief Program (TARP) authorized by Congress in the fall of 2008. It provided \$200 billion in equity injections to many large U.S. financial institutions. Admittedly, TARP had additional objectives, such as preventing runs and domino effects.

¹²A number of theoretical works have argued in favor of information sharing and transparency in lending markets, see Japelli and Pagano (2006) for a survey.

¹³The Funding for Lending Scheme (FLS) implemented in the U.K. in 2012 had a similar flavor by making public support conditional on lending. However, the difference is that this proposal focuses on loans made to new clients of a bank.

credit reallocation, but focuses on search frictions as opposed to the information gap.

A growing body of literature has provided clean evidence for differences in information on the same side of the market, for instance, between mortgage lenders in Stroebel (2015) or homeowners in Stroebel and Kurlat (2014). They show how more informed agents outperform others, either by lending against better collateral or better timing market movements in local housing prices. My focus on aggregate lending and the share of borrowers unable to obtain a loan is complementary to these papers. Moreover, a number of works have showed that soft information matters for lending, including Mian (2006), Liberti and Mian (2009), Botsch and Vanasco (2015), Rajan, Seru and Vig (2014), and Keys et al. (2010). Others have studied how adverse selection can change in crisis times, such as Malherbe (2013), Uhlig (2010) and Becker, Bos and Roszbach (2015), although none have quantified its effect on lending after a shock.

In the labor literature, Kahn (2014) finds evidence of asymmetric information across employers using compensation data, while Gibbons and Katz (1991) show that employees fired in plant closings as opposed to layoffs face shorter unemployment spells and receive higher post-displacement wages. As with the industrial organization literature estimating empirical models of informational frictions, such as David, Hopenhayn, Venkateswaran (2015), Einav, Jenkins and Levin (2012), and Einav, Finkelstein and Schrimpf (2010), I share the objective of quantifying the effect of these frictions beyond simply testing for their existence. Dickstein and Morales (2015) also estimate a model in which agents are more informed than the econometrician. Those papers, unlike this one, do not consider differences in information on the same side of the market, i.e. an information gap between lenders. Finally, this paper relates to the recent consensus that policy-makers should take a macro-prudential approach to regulating credit markets (Hanson et al., 2011). Specifically, I study the ability of relatively healthier banks to substitute for banks exposed to an idiosyncratic shock.

This paper is organized as follows. Section 2 describes the U.S. syndicated loan market and the impact of the financial crisis on relationships and credit reallocation. Section 3 develops a model

of firm borrowing and reallocation in which lenders have different information about borrowers. Section 4 explains the identification strategy in detail. Section 5 describes the estimation procedure and the results. Section 6 contains all counterfactual exercises. Section 7 concludes.

2 Relationships and Reallocation in the U.S. Corporate Loan Market

2.1 Data

The data comes from the DealScan database, which covers the syndicated corporate loan market in the United States. Studying the corporate loan market is interesting in itself given the role it plays in driving economic growth. Corporate borrowing has been shown to impact investment (Peek and Rosengree 2000, Chaney et al. 2012), firm employment (Chodorow-Reich 2014, Greenstone, Mas and Nguyen 2014), as well as innovation activity (Hombert and Matray, 2015). Syndicated loans play a central role in the American corporate loan market, and the Federal Reserve's Terms of Business Lending survey estimates that in recent years they account for about 50% of C&I lending with maturity more than one day, and 60% with maturity more than one year. Moreover, DealScan covers the issuance of new loans and, as opposed to bank balance sheet data, reflects the flow of credit in any given period.

The DealScan dataset is particularly suited to the study of banking relationships as it contains information at the loan level. In particular, it is possible to track which firm borrowed from which lenders before and after the crisis. Syndicated loans are typically large, and the median loan is about \$300 million in my sample. These loans are typically not made by a single lender but by a consortium referred to as a syndicate. Lenders in a syndicate are typically large banks that are divided between lead lenders and participants. Lead lenders provide a larger share of the funds and have more responsibilities in terms of reporting and monitoring.

I focus on the period around the bankruptcy of Lehman Brothers in September 2008.¹⁴ I divide the sample between a pre-crisis period spanning January 2004 to August 2008 and post-crisis period spanning October 2008 to December 2010. I include only loans made to non-financial, American firms used for financing the firm operations¹⁵.

An attractive feature of my sample is that it is not restricted to public firms, and includes about 60% of private firms that are more dependent on lending relationships. A limitation is that I cannot trace other forms of financing received by these firms during this period.¹⁶ However, about 90% of the lending agreements signed before the crisis include credit lines, which are flexible liquidity management tools that resemble credit cards offered to households. These credit lines allow the borrowers not to commit ex-ante to any loan size and are thus difficult to replace with other forms of financing, such as bond issuance.

2.2 The Impact of the Financial Crisis

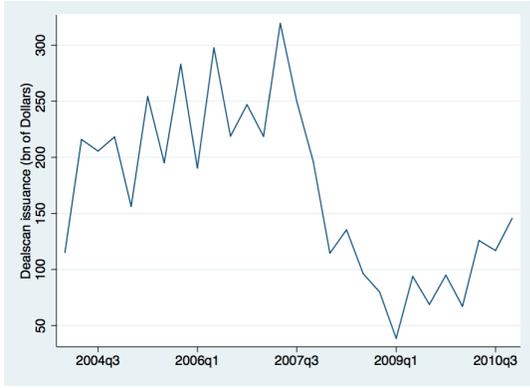
Like many other lending markets, the syndicated loan market suffered an unprecedented collapse after the financial crisis. The left panel of Figure 1 shows that the issuance of new loans was cut in half, from an average of about \$200 billion of new loans per quarter before the crisis to only \$100 billion afterwards. The right panel of Figure 1 shows that, although the DealScan sample tends to cover larger firms, it displays similar trends with aggregate C&I lending over the past ten years.

An important feature of this market is that this collapse occurred at the *extensive margin of credit*. In fact, loan size remained stable; it was a sharp decrease in the number of firms receiving a new loan that depressed lending volume after the crisis. To see this, I define the market *lending rate* as a measure of the extensive margin response. The lending rate can be computed for any

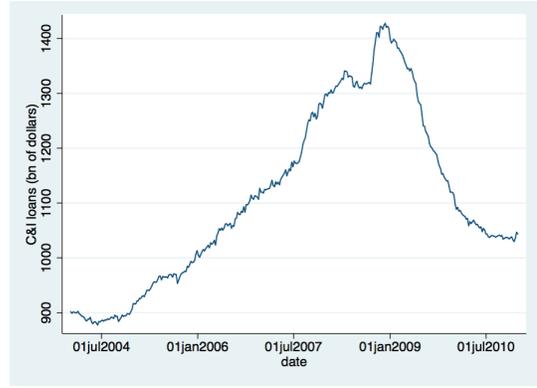
¹⁴Chodorow-Reich (2014) use the same event to divide his sample.

¹⁵Loans are classified in this way when the purpose of the loan is declared as "working capital" or "corporate purposes", as opposed to M&A activity or debt restructuring.

¹⁶Only about half of firms in my sample are in the Compustate database.



(a) DealScan issuance



(b) All C&I lending (Federal Reserve Data)

Figure 1: Aggregate corporate lending (in 2008 U.S.\$): 2004-2010

calendar year t and is defined as follows:

$$Lending\ rate_t = 2 * \% \text{ of firms with a loan in years } [t - 4, t] \text{ that receive a new loan in } [t, t + 2]$$

The lending rate captures how easy it is for firms that have borrowed previously to find a new loan. The pre-period time length is chosen to match the typical maturity of loans before the crisis, which is just less than four years. The post-period time length is chosen to be two years because firms typically sign a new loan two years before their existing loan expires. The factor two in the formula accounts for the difference in pre and post window size. This normalization ensures that a lending rate of 1 implies stable lending at the extensive margin.¹⁷

As displayed in Table 1, the lending rate collapsed in 2008 to reach 0.65 down from slightly above 1 in 2004, and had almost recovered by 2010. Change in loan terms are shown in Table 2: while loan size remained stable, borrowing became significantly more expensive and the average loan maturity fell from about four years down to three.¹⁸ There was also a moderate drop in the

¹⁷This measure accounts for new loans that are occasionally misclassified as loan modifications. For instance, the renewal of a two-year credit line can sometimes be reported as a two-year extension of an existing credit line. In all that follows, I classify a firm as borrowing after the crisis if it receives a new loan or a modification of an existing loan granting extra funds.

¹⁸I follow most of the literature in using the all in drawn spread as a measure of the price of credit, although Berg et al. (forthcoming) have noted that fees play an important role as well.

Year	Lending rate	% from new lender
2004	1.10	12 %
2008	0.65	16 %
2010	0.93	14 %

Note: The lending rate in year t is computed as $2\times$ share of firms with a loan in years $[t-4, t]$ that receive a new loan in $[t, t+2]$. A loan in the post-period is classified as made by a new lender if no lead lender of its lending syndicate was a lead lender of its last pre-period syndicate. The sample is restricted to U.S. non-financial firms which list the reason for borrowing as "working capital" or "corporate purposes".

Table 1: The extensive margin of credit: 2004-2010

	Pre-crisis (Jan 04-Sept 08)		Post-crisis (Oct 08-Dec 10)		% change in mean
	Mean	Std. Dev.	Mean	Std. Dev.	
Loan size (\$M)	441	841	459	770	4.1%
Spread (bp)	158	104	294	128	86.1%
Maturity (years)	3.8	1.55	3	1.35	-21.1%
#Lenders in syndicate	5.3	3.6	4.2	4	-20.8%

Note: This table includes only firms that received a loan in the pre-crisis period. The post-crisis loan is the first new loan received in the post-crisis period (if any). The sample is restricted to U.S. non-financial firms which list the reason for borrowing as "working capital" or "corporate purposes".

Table 2: Change in loan terms after the crisis

size of firms' lending syndicates.

2.3 Relationship Lending and Credit Reallocation

An important aspect of this market is the prevalence of banking relationships. Because loan terms and covenants need to be tailored to the specific borrower, there is a comparative advantage for a bank to repeatedly lend to the same firm over time. These relationships are valuable as lenders acquire better knowledge of borrowers and how to efficiently adjust loan terms. This comparative advantage suggests that lending relationships are "sticky" and that forming new relationships is difficult.

A key feature of the DealScan dataset, is that it can be used to trace banking relationships.

In particular, I can observe from which lenders a firm borrowed before the crisis and ask whether it received a loan post-crisis from the same lenders. Moreover, in the case in which an existing relationship was ended, I can observe whether the firm was able to form a new relationship or received no loan at all. In order to classify firms in this way, I identify renewal and formation of relationships by comparing the last pre-crisis loan received by that firm to its first new post-crisis loan (if any). Moreover, because of their special role as information gatherers, I restrict attention to lead lenders when classifying new relationships. More precisely, a firm is classified as "borrowing from a new lender" if no lead lender in its first post-crisis loan syndicate was a lead lender of its last pre-crisis loan syndicate. Section 5.5 shows the effect of adopting a different classification.

The stickiness of banking relationships is evident in this market. The last column of Table 1 shows the historical shares of new loans made by new lenders. This share is strikingly small, ranging from 12% in 2004 to 16% in the midst of the crisis, and can be taken as a first piece of evidence that forming new banking relationships is difficult.

The difficulty of finding new lenders suggests that bank shocks impose a substantial cost on borrowers that see their existing relationship ended. The focus of this paper is precisely on *credit reallocation*: how easily can borrowers find a new lender to compensate for a shock received by their existing lender? A friction in this reallocation implies that *bank-specific shocks* reduce lending in the *aggregate*. The objective of this paper is to quantify the share of the fall in aggregate lending in this market that is due to an informational friction impeding credit reallocation. While the last column of Table 1 shows that there was slightly more reallocation during the crisis, the question is how much more would have occurred absent this friction? How smaller would the fall in aggregate lending have been?

2.4 Informational Frictions

How do informational frictions affect credit reallocation? Consistent with the literature on banking relationships, the key idea is that not all lenders share the same information about borrowers.

Lenders that have lent to a firm in the past have acquired private information in the course of the relationship that is unknown to other lenders. I dub this difference in information across lenders the *information gap*.¹⁹

The information gap affects credit reallocation through the following key channel. Because lenders have private information about their existing borrowers, they are able to selectively choose which relationships to end when faced with a shock that forces them to reduce lending. This "cream-skimming" implies that borrowers whose relationship ended face *stigma*: potential new lenders are wary that these borrowers are of lower quality. This negative signal makes it difficult for borrowers to switch lenders and the information gap leads to imperfect credit reallocation.

An important implication is a *selection effect*: borrowers coming from the most affected lenders face *less* stigma. Intuitively, the most affected lenders have to end a large number of relationships including some with relatively good borrowers. This selection effect corresponds to the following empirical prediction: conditional on having its pre-crisis relationship ended, the probability that a firm borrows from a new lender after the crisis *increases* with its pre-crisis lender's exposure to the crisis.

There is evidence that this effect was at work in this market after the crisis. I measure lenders' exposure to the crisis by the relative change in lending at each bank after the Lehman bankruptcy that occurred in September 2008. For each lender, I then count the number of loans made in the post-crisis period to firms that received a loan pre-crisis (from this particular lender or any other lender in the sample). I divide this number by the total number of loans made in the pre-crisis period by this lender, adjusting for the asymmetric time window between the two periods. Moreover, because these loans are syndicated across multiple lenders, I weight each element in the

¹⁹Sharpe (1990), Rajan (1992) and Detragiache et al. (2000) are example of theoretical papers studying the impact of the information gap on firms.

numerator and the denominator by the loan share of that particular lender:²⁰

$$\delta^l = 1 - 2 \times \frac{\#\text{post-crisis loans made by lender } l \text{ to firms that borrowed pre-crisis}}{\#\text{pre-crisis loans made by lender } l} \quad (1)$$

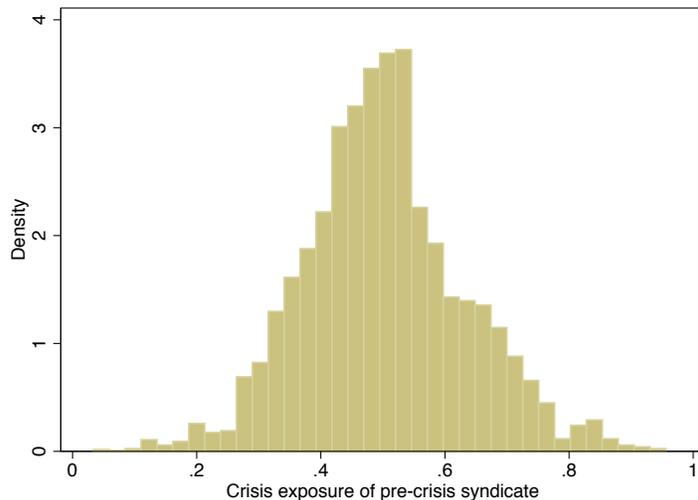
A larger δ^l implies that fewer loans are made post-crisis and indicate a more affected lender; a constant loan supply at the bank level would result in a δ^l of zero. Because syndicated loans are made by multiple lenders, I transform this lender-level measure into a firm-level measure by exploiting the structure of the firm's pre-crisis syndicate in the same way as Chodorow-Reich (2014). For each firm f , I compute a weighted average of lenders δ^l , using as weights the loan shares $\omega^{l,f}$ of each lender in the syndicate s^f of the last pre-crisis loan of this particular firm. This yields a clear measure of the credit supply shock faced by this firm:

$$\delta^{s^f} = \sum_{l \in s^f} \omega^{l,f} \delta^l \quad (2)$$

As reported in Figure 2, the mean of this measure is about 50%, which is in line with the aggregate dollar figure presented in Figure 1. Moreover, with a standard deviation of 13%, firms face a variety of supply shocks, consistent with the idea that the need for reallocation arises after a crisis. Finally, for ease of exposition, in the rest of the paper I will often refer to a syndicate as a "bank" or a "lender" and write δ^b instead of δ^s , even though it is understood that firms borrow from multiple lenders at once.

Consistent with the selection effect, Figure 3 shows that among firms that saw their relationship end, firms coming from more affected lenders are more likely to obtain a loan from a new lender relative to firms coming from less exposed lenders. Table 8 in the Appendix replicates these findings in a regression framework controlling for borrower characteristics and past loan terms. This pattern is direct evidence that new lenders are learning from the fact that a relationship has

²⁰Because the data on loan shares is occasionally missing, I follow the method introduced in Chodorow-Reich (2014) to recover them via an imputation. This measure excludes loan modifications, as there is no way to consistently recover loan shares in this case.



Note: The crisis exposure of a firm's pre-crisis lender is computed as the weighted average of the relative drop in lending between 2004-2008 and 2008-10 of each lender in the firm's last pre-crisis lending syndicate, weighted by the loan shares of each lender. The sample is restricted to U.S. non-financial firms that list the reason for borrowing as "working capital" or "corporate purposes."

Figure 2: Distribution of firms' pre-crisis lender crisis exposure

ended.²¹ Note also that this pattern is at odds with the idea that bad borrowers were matched with less healthy lenders. Indeed, if that was the case, the correlation between pre-crisis lender health and new relationships would go the other way: borrowers coming from less affected lenders would be more likely to borrow from a new lender.²²

However, this correlation alone cannot identify the information gap, as it is also partly driven by information *common to all lenders*. In fact, a new lender is more likely to accept borrowers coming from the most affected lender for two reasons: (i) they are inferred to be better along the dimension that is privately observed by their previous lender; and (ii) they are objectively better along the dimension that is commonly observed by all potential new lenders. Given that such common information is likely to exist, an important contribution of my approach is to be able

²¹Shlain (2015) provides evidence of the same pattern looking at equity issuance during the crisis.

²²While the focus of this paper is on the extensive margin of credit, a comparison of the characteristics of post-crisis loans made to new borrowers relative to repeated borrowers is consistent with cream-skimming. Controlling for lender and borrower characteristics, Table 9 in the Appendix shows that loans made to new borrowers are 26% smaller than those made to repeat borrowers. Loans to new borrowers also carry a larger spread by about 23 basis points and are 3 percentage points more likely to be secured by collateral. To the extent that these loan terms are informative about borrower quality, this reveals that new borrowers are less creditworthy than repeat borrowers.

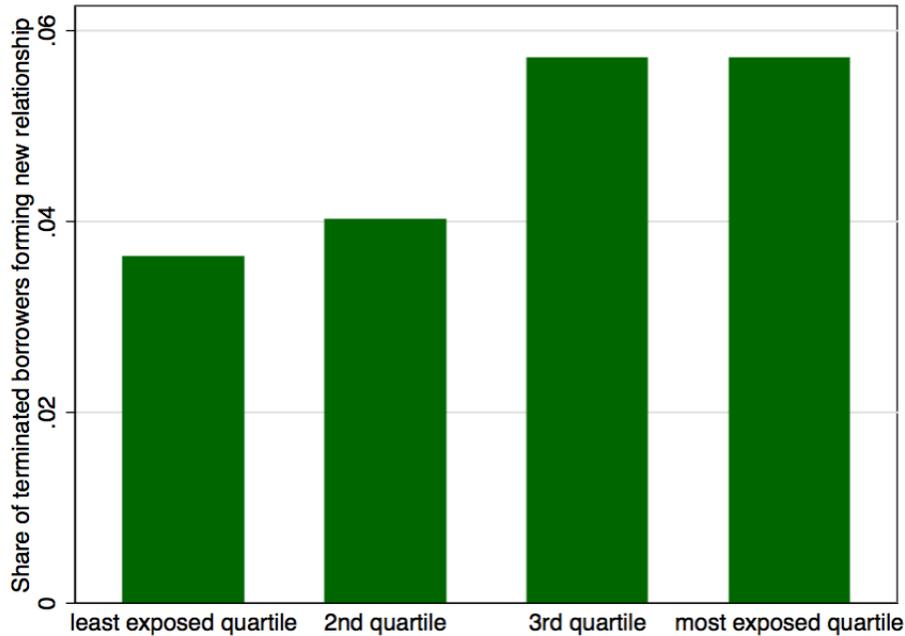


Figure 3: Pre-crisis lender crisis exposure and the formation of new relationships

Note: This sample includes only borrowers who did not renew their previous relationship after the crisis. A borrower is classified as renewing a relationship if at least one lead lender of its post-crisis lending syndicate was a lead lender of its last pre-period syndicate. Other borrowers receiving a new loan after the crisis are classified as forming a new relationship. The crisis exposure of a firm's pre-crisis lender is computed as the weighted average of the relative drop in lending between 2004-2008 and 2008-10 of each lender in the firm's last pre-crisis lending syndicate, weighted by the loan shares of each lender. The sample is restricted to U.S. non-financial firms that list the reason for borrowing as "working capital" or "corporate purposes."

to correct for this source of bias when estimating the information gap, as discussed in detail in Section 4.

To implement this strategy, I introduce a two-stage discrete choice model of firm borrowing after the crisis. The key ingredient of the model is the existence of three layers of information: (i) all lenders have some information about borrowers, but (ii) each lender has private information about its existing borrowers, and (iii) the econometrician observes neither.

3 A Model of Lending and Credit Reallocation with Informational Frictions

The framework takes existing relationships as given and aims to explain the pattern of lending post-crisis. It adds to classical models of credit markets with informational frictions by incorporating heterogeneity on the supply side, both in terms of cost of funds and private information. The model aims to be empirically estimated and balances the need to capture the economic forces behind the informational friction with the need to be estimated with firm-level data alone.

3.1 Setup

Consider a firm f with an existing relationship with lender b . Post-crisis, the firm has a new project that requires financing (or an older project that requires new funds) and can ask for a new loan. Assume that the firm first tries to renew its existing relationship and bargains for a new loan with its pre-crisis lender. If the lender instead chooses to end the relationship, the firm has the possibility of trying to form a new relationship and obtain a loan from a new lender.²³ Figure 4 illustrates the setup.

²³Institutional details justify this timing assumption. Shopping around lenders is difficult as corporate loans must be tailored to the specific borrower, and loan terms offered by potential lenders are not publicly available. Firms tends to first bargain with their existing lender to save on transactions costs associated with identifying a potential new lender, as opening a negotiation takes time and involves substantial communication costs.

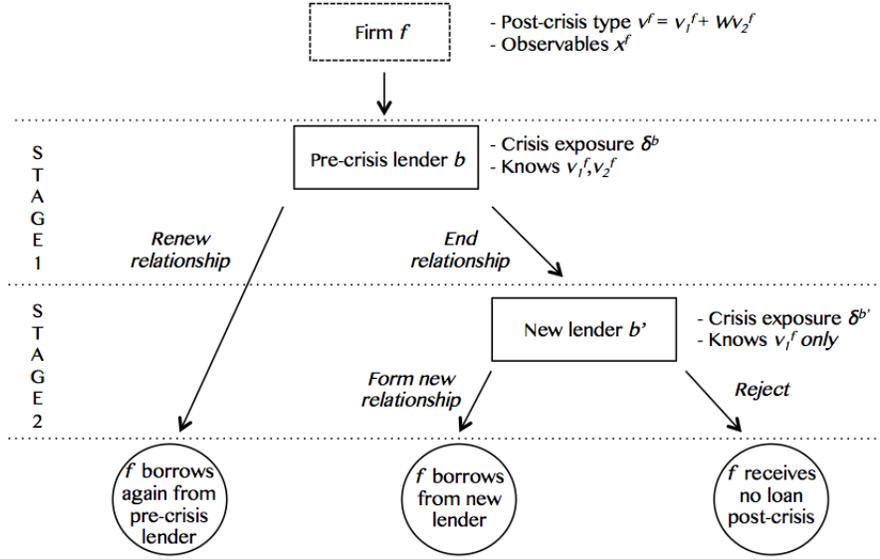


Figure 4: The model of firm post-crisis borrowing

Lending generates a surplus s that depends on both firm and lender characteristics and that can be divided in the pair. A loan is made if $s > 0$, i.e. lending has a positive NPV. Assume the following general form where surplus in a pair depends on four components:

$$s(\nu^f, x^f, \mu_0, \delta^b)$$

- *Firm unobservable post-crisis type ν^f* : This term is at the core of the informational friction. It captures "soft" information about the borrower that not all lenders have access to equally.²⁴ Importantly, this term captures the desirability to lend to the firm *after the crisis*. In particular, it is possible that firms that borrowed in the past should no longer receive a loan, for instance because the demand for the firm's end product has fallen.
- *Firm observables x^f* : This term captures "hard information" that is available in DealScan.

Firm characteristics can impact surplus in two ways: (i) borrower creditworthiness, and (ii)

²⁴From the start, the literature has emphasized the key role that banking relationships play in producing information about borrowers. Nevertheless, ν^f can also contains some hard information that is shared by all lenders, but is unobservable to the econometrician. Exactly how much of soft vs. hard information is in ν^f is precisely the focus of this paper.

demand for bank loans. Banks are naturally less willing to lend to firms with a poor track record or in a fledging industry. However, it can also be the case that some "good" firms are unwilling to borrow because they have enough financial slack, or other funding opportunities outside of the banking sector. I will not try to distinguish between these two forces and will include a large number of firm controls available in DealScan to account for them. These controls include firm characteristics such as public ownership, sales, and industry, as well as rich information on loans received before the crisis. Loan terms include pre-crisis loan size and spread, whether it was collateralized but also whether it covers the post-crisis period, as well as whether the firm had multiple pre-crisis loans.

- *Aggregate shock μ_0* : This term captures other factors that reduced lending after the crisis, independently of informational frictions. It accounts for the financial turmoil that affected all lenders equally, as well as demand shocks for end products that affects all firms. It also captures other type of aggregate shocks to lending, such as "uncertainty" shocks or events in other lending markets.
- *Lender-specific crisis exposure δ^b* : This term captures the credit reallocation problem: beyond the aggregate shock μ_0 , some lenders were more affected than others. The key question is whether borrowers that see their relationship end are able to reallocate toward new, relatively healthier lenders. Empirically, I measure δ^b with the relative fall in lending in the lending syndicate, as defined in Section 2.4.

3.2 Information hierarchy

Conceptually, the key aspect of the model is the existence of an *information hierarchy*: not all agents have the same information about firm unobservable type ν^f post-crisis. To make this hierarchy transparent, I decompose the firm type as follows:

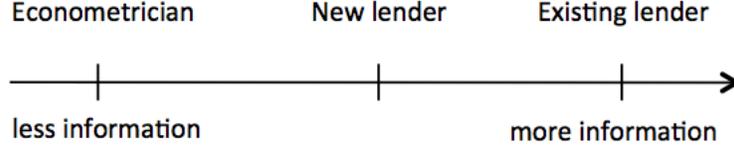


Figure 5: Information hierarchy

$$\nu^f = \nu_1^f + \mathcal{W}\nu_2^f$$

Assume ν_1^f and ν_2^f have distributions F_1 and F_2 , both with mean zero and that:

- ν_1^f is known to *all* lenders
- ν_2^f is known only to the firm's pre-crisis lender
- the econometrician knows neither ν_1^f nor ν_2^f

The main object of interest is the *information gap* \mathcal{W} that represents the weight on the pre-crisis lender private information.²⁵ Intuitively, there is an informational hierarchy and three levels of information, as depicted in Figure 5. At one extreme is the firm's pre-crisis lender, who knows both ν_1^f and ν_2^f , as well as observables x^f . At the other extreme is the econometrician, who knows only x^f . \mathcal{W} measures how informed new lenders are relative to these two extremes. If $\mathcal{W} = 0$, all lenders share the same information about the firm and the information gap is zero. As \mathcal{W} increases, so does the information gap between the firm pre-crisis lender and its potential new lenders.

The formulation above assumes that the components of firm post-crisis types ν_1^f and ν_2^f are homogenous across lenders, i.e. that there is no match-specific component. While match specificity is likely to exist in practice, this simplification does not endanger my identification strategy. Indeed,

²⁵The factor \mathcal{W} is not separately identified from the variance of ν_2^f , hence for the rest of the paper I impose the normalization that $Var[\nu_2^f] = 1$. The standard deviation of the privately observed component is therefore \mathcal{W} .

the key moment that identifies the information gap is the selection effect: borrowers coming from the most affected lenders are more likely to find a new lender. In other words, the decision of a firm's pre-crisis lender to not renew its relationship influences the decision of other lenders. This pattern cannot be rationalized by a match-specific term, as by definition it only affects a particular lender and carries no information relevant to other lenders.

3.3 Equilibrium Post-crisis Lending

Recall that a firm can obtain a loan after the crisis in two ways. It can first try to renew its existing relationship and receive a new loan from its pre-crisis lender. If that fails, the firm has the option to try to form a new relationship and obtain a loan from a new, but less informed, lender. This section solves for the equilibrium of these two stages in turn.

In order to ensure uniqueness of equilibrium, I make the following weak technical assumptions:

Technical conditions (TC)

1. F_2 is log-concave.²⁶
2. (i) $\lim_{\nu \rightarrow \nu_{min}} s(\nu, \mu_0, x, \delta) < 0$; (ii) $\lim_{\nu \rightarrow \nu_{max}} s(\nu, \mu_0, x, \delta) > 0$
3. (i) s is (weakly) concave in ν ; (ii) $\partial s / \partial \nu$ is positive and uniformly bounded away from zero.

All omitted proofs are in the Appendix.

3.3.1 First stage: relationship renewal

First, the firm can try to renew its relationship with its pre-crisis lender and obtain a new loan after the crisis. The pre-crisis lender knows ν^f and the loan is granted if there is positive surplus in the pair given this information. The relationship is renewed for firms with sufficiently high post-crisis type.

²⁶Many commonly used distributions are log-concave, including the normal, uniform, logistic, exponential, gamma and beta distributions.

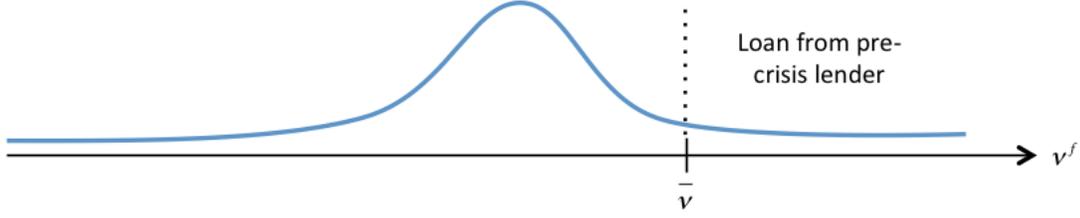


Figure 6: Stage 1: renewing existing relationships.

Proposition 1 (*Cream-skimming*): *Firm f renews its relationship with lender b if:*

$$s(\nu^f, x^f, \mu_0, \delta^b) \geq 0 \iff \nu^f \geq \bar{\nu}(\mu_0, x^f, \delta^b) \quad (3)$$

Proof: Follows from $\partial s / \partial \nu^f > 0$ and TC 2.

This corresponds to a simple cutoff rule for renewing relationships and Figure 6 illustrates the equilibrium of the first stage. Firms above the cutoff renew their relationship, while firms below are left looking for a new lender. Because the lender has access to private information, he selectively chooses to renew its relationship with its best borrowers.

The cutoff $\bar{\nu}$ naturally depends on firm and lender characteristics, as well as the aggregate shock μ_0 . In particular, lenders that are more affected by the crisis renew fewer relationships: the cutoff moves to the right. This comparative statics is the origin for the selection effect that plays an important role in the second stage equilibrium.

3.3.2 Second stage: new relationship formation

Firms that saw their relationship end in stage 1 can try to form a new relationship and borrow from a new lender b' . However, the new lender can only observe ν_1^f and not ν_2^f . The information gap \mathcal{W} measures how important this unobservable component is to predict the firm's type.

The new lender also knows the firm's observable characteristics x^f and that it did not renew

its existing relationship. In particular, the set of firms looking for a new lender is selected:

$$\nu^f \leq \bar{\nu}(\mu_0, x^f, \delta^b) \iff \nu_2 \leq \frac{\bar{\nu} - \nu_1}{\mathcal{W}} \quad (4)$$

The surplus from forming a new relationship, conditional on new lender's information is thus:

$$\mathbb{E}[s|\nu_1, \nu_2 \leq \frac{\bar{\nu} - \nu_1}{\mathcal{W}}] = \int_{\nu_2 \leq \frac{\bar{\nu} - \nu_1}{\mathcal{W}}} s(\nu_1 + \mathcal{W}\nu_2, \mu_0, x^f, \delta^b) \frac{dF_2(\nu_2)}{F_2(\frac{\bar{\nu} - \nu_1}{\mathcal{W}})} \quad (5)$$

Lemma 1: *The expected surplus is strictly increasing in ν_1 .*

This lemma implies that new lenders use a cutoff rule to form a new relationship:

Proposition 2: *Firm f coming from lender b forms a new relationship with lender b' if:*

$$\mathbb{E}[s|\nu_1, \nu_2 \leq \frac{\bar{\nu} - \nu_1}{\mathcal{W}}] \geq 0 \iff \nu_1^f \geq \nu^*(\mu_0, x^f, \delta^b, \delta^{b'}) \quad (6)$$

Proof: Follows from Lemma 1.

Because the new lender is less informed, the key difference with the first stage is that lending is contingent on ν_1^f as opposed to $\nu^f = \nu_1^f + \mathcal{W}\nu_2^f$. Importantly, the cutoff ν^* depends on the firm's pre-crisis lender crisis exposure δ^b because of the selection effect:

Proposition 3 (Selection effect): *ν^* decreases with the firm's pre-crisis lender crisis exposure δ^b .*

Proof: Follows immediately from the fact that $\bar{\nu}$ is increasing in δ^b and that F_2 is log-concave.

Intuitively, new lenders are more likely to lend to borrowers that ended their relationship with the most affected lenders. These borrowers are on average of better quality and therefore face less stigma.

3.4 The Effect of the Information Gap on Lending

The previous analysis can be used to show how the information gap affects lending. An important result is that new lenders adopt stricter lending rules because of the information gap:

Proposition 4: If $\mathcal{W} > 0$, the cutoff $\nu^*(\mu_0, x^f, \delta^b, \delta^{b'})$ used by less informed lenders is higher than the full information cutoff $\bar{\nu}(\mu_0, x^f, \delta^{b'})$.

Intuitively, new lenders understand that leaving a relationship is a signal in itself that the pool of new borrowers is worse than average. New lenders therefore adopt stricter lending rules that reflect this stigma.

Figure 7 illustrates the effect of the information gap on lending. The x-axis represents the commonly observed component of firm's post-crisis type ν_1^f , and all firms to the right of the cutoff ν^* receive a loan from a new lender. The y-axis represents firms' true type $\nu^f = \nu_1^f + \mathcal{W}\nu_2^f$. If the information gap \mathcal{W} were zero, all firms, denoted by black dots, would lie on the 45 degree line. Instead, when new lenders have less information, firms are scattered around the diagonal. If the information gap were zero, lenders would lend to firms whose *true* type is above the cutoff $\nu^{\text{full info}}$.

The two cutoff rules delineate three areas. The north-east corner corresponds to firms that are good enough along all dimensions to receive a loan even if new lenders have less information. On the other hand, the north-west corner corresponds to underfunding: these firms are unable to receive a new loan because of the information gap. The firms are good overall, but happen to be worse along the commonly observed dimension ν_1 . Interestingly, there is a third region of overfunding: some firms happen to be particularly good only along the dimension ν_1 . As long as the information gap is not too large, firms are concentrated along the diagonal and underfunding is thus expected to dominate empirically. In fact, the objective of this paper is to estimate the amount the underfunding due to the information gap.

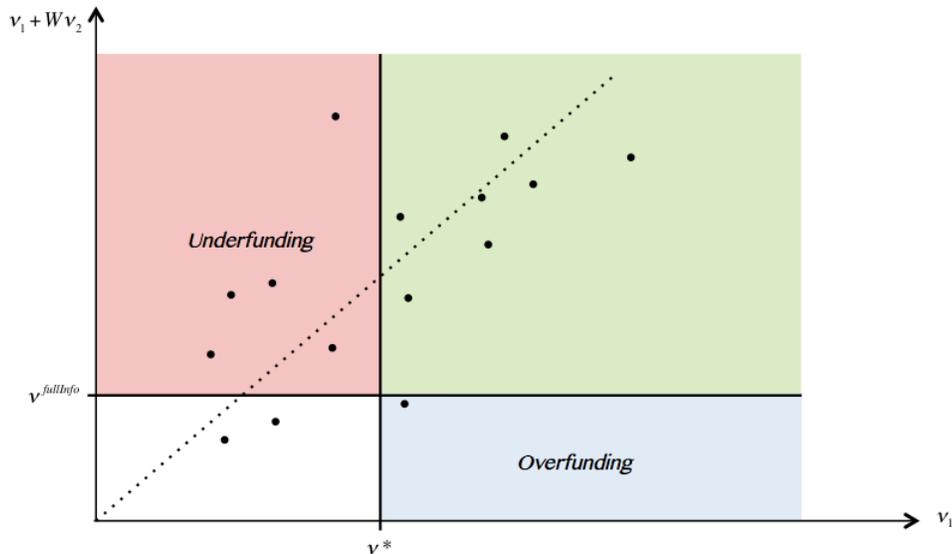


Figure 7: The effect of the information gap on lending

4 Identification Strategy

To quantify the effects of the information gap on credit reallocation, I estimate the model described above. Formally, the equilibrium corresponds to a two-stage discrete choice model of firm borrowing after the crisis. In the first stage, firms try to renew their relationship with their existing lender. If a borrower fails to receive a new loan from its existing lender, it can turn to new lenders in the second stage. The information gap impacts second stage lending.

The identification strategy relies on two sources of cross-sectional variation in the data: (i) some lenders have lent to a firm in the past, while other have not; and (ii) lenders had different exposure to the crisis. I combine these two sources of variation to credibly identify the information gap between lenders.

I focus on a prediction that is unique to informational frictions: the selection effect described in Section 2.4.²⁷ The idea is that, among borrowers that saw their pre-crisis relationship ended,

²⁷Importantly, other frictions are unlikely to drive this cross-sectional evidence. In particular, fixed costs of setting new relationships (due diligence, search costs) are unlikely to vary with the crisis exposure of the firm's previous lender. Moreover, match-specific capital is by definition unrelated across lenders, so this effect alone cannot explain why new lenders' decision depends on the firm previous lender's exposure.

firms coming from the most affected lenders find it easier to find a new lender because they face less stigma. To identify the information gap, I thus exploit how cross-sectional variation in lenders' exposure to the crisis explains the probability of forming a new relationship, *within the subsample* of firms that did not renew their pre-crisis relationship. A larger information gap implies a larger correlation: lending decisions of previous lenders carry more information for new lenders.

However, this correlation alone cannot identify the information gap, as it is also partly driven by information common to all lenders. As the econometrician cannot directly observe lenders' information, it is not possible to separately identify the information gap from the common information component using the reduced form correlation alone.

More precisely, recall that in the language of the model, the true firm type is $\nu^f = \nu_1^f + \mathcal{W}\nu_2^f$. To see why common information ν_1^f implies a potential bias, consider the new lender's problem of inferring the firm post-crisis type ν^f . Its conditional expectation given its information is given by:

$$\mathbb{E}[\nu^f | I^b] = \nu_1^f + \mathcal{W} \underbrace{\mathbb{E}[\nu_2^f | \nu^f \leq \bar{\nu}(\delta^b)]}_{\text{selection effect}}$$

These two terms correspond to the two sources of information that the new lender has access to: the common information ν_1^f and the fact that leaving a relationship is a signal in itself. The second term incorporates the selection effect described above: the exposure δ^b of the firm's pre-crisis lender affects the new lender's inference about ν_2^f . This comparative statics is what identified \mathcal{W} : the larger the information gap \mathcal{W} , the stronger the effect of the pre-crisis lender's crisis exposure on the probability to form a new relationship.

However, ν_1^f is known to the new lender, but *unobservable to the econometrician*. Intuitively, it represents an "error term" and accordingly, the reduced form correlation is unbiased only if $\delta^b \perp \nu_1^f$, i.e. the commonly observed part of firm's type is uncorrelated with its pre-crisis lender's exposure. This is clearly not the case: only a subset of firms are not able to renew their relationship. Recall

that a firm is left looking for a new lender if:

$$\nu_1^f + \mathcal{W}\nu_2^f \leq \bar{\nu}(\delta^b)$$

which implies a correlation between ν_1^f and δ^b . In fact, the bias in the reduced-form correlation is larger when common information ν_1^f is more important.

To overcome this challenge, this paper relies on an identification strategy that exploits a comparison with the sample of borrowers who renewed their relationships. The key idea is that relationship renewal can be used for *benchmarking* lenders' behavior: renewal reflects how lenders lend to borrowers they have private information about. Intuitively, if there were no information gap, the lending decision of new lenders should match the lending decision rule of informed lenders.

Concretely, this approach requires estimating relationship renewal, as in the first stage of the model. I estimate the probability that a firm renews its relationship with its pre-crisis lender, as a function of the lender's exposure δ^b and firm characteristics x^f . In other words, the first stage estimates the function $\bar{\nu}(\mu_0, x^f, \delta^b)$ that determines which firms renew their relationship:²⁸

$$\text{firm } f \text{ renews relationship with lender } b \iff \nu^f \geq \bar{\nu}(\mu_0, x^f, \delta^b) \quad (7)$$

First stage estimates are used as inputs in the second stage estimation equation:

$$\mathbb{P}(f \text{ borrows from a new lender}) = \mathbb{P}(\nu_1^f \geq \nu^*(\delta^b, \delta^{b'}, x^f, \mathcal{W}) | \nu^f \leq \bar{\nu}(\delta^b, x^f)) \quad (8)$$

where ν^* is lending rule used by new lenders given information gap \mathcal{W} .

Pre-crisis lender exposure δ^b is correlated with second stage borrowing through two channels:

(i) its correlation with the lending rule ν^* ; and (ii) its correlation with common information ν_1^f ,

²⁸This setting is ideal for benchmarking because this lending rule is unlikely to be lender-specific, as lenders are not divided in groups of "informed" vs. "uninformed". In fact, the same lender is informed about some borrowers, but uninformed about others.

as reflected on the conditioning $\nu^f \leq \bar{\nu}(\delta^b, x^f)$. Under the null hypothesis of no information gap, pre-crisis lender exposure does not *directly* affect the lending rule: ν^* is independent of δ^b . In this case, the correlation only stems from the relationship between ν_1^f and δ^b that arises from the selection of firms reaching the second stage.²⁹ If this correlation alone matches the correlation observed in the data, the information gap is estimated to be zero.

More generally, the difference between the lending rule ν^* used by new lenders and the lending rule $\bar{\nu}$ used by previous lenders represents a residual that is unexplained by common information. The information gap is estimated from the correlation between this residual and pre-crisis lender exposure in the cross-section of borrowers. The estimated magnitude of the information gap matches the residual correlation observed in the data that is unexplained by common information. The maintained assumptions are that the distribution of borrower unobservables and the lending rule (as a function of borrower and lender characteristics) are common across lenders.

Importantly, this cross-sectional approach is valid even though the mean of this residual is likely affected by other frictions, such as fixed costs of establishing a new relationship, search costs or match-specific capital. As opposed to the literature that identifies informational frictions by comparing firms with different degrees of opacity, this approach relies on comparing how lenders with different information would treat the *same* firm. The two-step approach bears some resemblance to econometric models in the line of Heckman (1979) but is used to account for differences in information among agents, a feature that is absent from these models.

5 Estimation and Results

5.1 Overview

For the purpose of estimation, I make the following parametric assumptions:

²⁹For any parametric assumption on the distribution of borrower unobservables ν_f , the cutoff rule determined by $\bar{\nu}$ is sufficient to characterize the conditional distribution of ν_1^f for firms reaching the second stage.

- Linear surplus: $s = \nu^f + x^f \mu + \mu_0 + \delta^b \beta$
- Normality: $\nu_1^f \sim \mathcal{N}(0, \sigma_1^2)$, $\nu_2^f \sim \mathcal{N}(0, 1)$, so that $\nu^f \sim \mathcal{N}(0, \sigma_1^2 + \mathcal{W}^2)$

In this setting, the following decomposition makes the interpretation of the information gap clear:

$$\underbrace{\text{Var}[\nu^f]}_{\text{unobservable to econometrician}} = \underbrace{\sigma_1^2}_{\text{observed by all lenders}} + \underbrace{\mathcal{W}^2}_{\text{unobservable to new lenders}} \quad (9)$$

Concretely, the information gap corresponds to a decomposition of residual variance: how much of what is unobservable to the econometrician is also unknown to new lenders. Because the units of the model are arbitrary, only a *relative* measure of information is identified:

$$\frac{\text{Std. deviation of unobservables to new lenders}}{\text{Std. deviation of unobservables to econometrician}} = \frac{\mathcal{W}}{\sqrt{\sigma_1^2 + \mathcal{W}^2}} \in [0, 1] \quad (10)$$

As the next section shows, the natural normalization is to impose $\sigma_1^2 + \mathcal{W}^2 = 1$. \mathcal{W} therefore captures the relevant measure of relative information.

I estimate the parameters $(\mathcal{W}, \beta, \mu)$ using a two-stage discrete choice model of firm borrowing after the crisis. In the first stage, I estimate the probability that a firm renews its relationship with its pre-crisis lender. In the second stage, I estimate the probability that a firm borrows from a new lender, conditional on seeing its relationship ended.

5.2 First Stage: Relationship Renewal

The firm's pre-crisis lender knows the true post-crisis type ν^f and renews its relationship based on a linear cutoff rule:³⁰

$$\nu^f \geq -\delta^b \beta - x^f \mu$$

³⁰For more compact notation, from now on I include the aggregate shock μ_0 in the vector of coefficients μ by extending the firm observables x^f to include a constant term.

The probability that firm f renews its relationship with lender b is thus given by:

$$\begin{aligned}\mathbb{P}(\text{borrow from pre-crisis lender}) &= \mathbb{P}(\nu^f \geq -\delta^b\beta - x^f\mu) \\ &= \Phi(\delta^b\beta + x^f\mu)\end{aligned}$$

where $\Phi(\cdot)$ is the normal cdf. With the usual normalization $\sigma_1^2 + \mathcal{W}^2 = 1$, this first stage estimation equation corresponds to a standard probit model. I therefore estimate the coefficients β and μ on lender and firm characteristics via probit regression. The measure of bank-specific exposure δ^b is the relative change in lending after the crisis by the firm's pre-crisis syndicate, as describe in Section 2.4. The vector of firm observables x^f contains indicators for whether the borrower is public, reports sales over the median, is in the manufacturing sector, has an existing loan that covers the post-crisis period, and has multiple pre-crisis loans. In addition, I include rich information pertaining to the last pre-crisis loan terms: spread, size, whether it was secured by collateral, and whether there were multiple lead lenders or two or less participants in its syndicate.

Results are presented in Table 3. The coefficient on pre-crisis lender exposure $\hat{\beta}$ is significant and equal to -3.02. The interpretation is that a one standard deviation increase in pre-crisis lender exposure decreases the probability of renewing its relationship by 3 percentage points, or about 15% of the average renewal rate. The economic and statistical significance of this measure of bank crisis exposure justify its use in the second stage to estimate the information gap. Moreover, firms that are public or large find it easier to renew their relationship.

Identifying β . The identification assumption for the first stage is that δ^b is orthogonal to unobservable post-crisis characteristics of borrower quality and demand ν^f . This identifying assumption is common to the literature that studies the firm-level effects of credit supply shocks. The identification threat is that banks that were affected the most by the crisis were matched with corporate borrowers that concurrently received a negative shock to their creditworthiness. Since the crisis originated in the real estate market, it is at least plausible in this particular case that

	Outcome: Borrow from pre-crisis lender		
Pre-crisis lender's exposure	-3.86***	-3.52***	-3.02***
	(0.61)	(0.63)	(0.67)
Public		4.54**	2.96**
		(1.45)	(1.46)
High sales		5.82**	3.87**
		(1.48)	(1.59)
Existing loan covers the crisis		-1.78	-1.09
		(1.31)	(1.33)
Multiple pre-crisis loans		9.95***	8.83***
		(1.30)	(1.32)
Manufacturing		0.98	0.77
		(1.33)	(1.32)
Pre-crisis loan terms	-	-	Yes
Mean of dependent variable	21.17%	21.17%	21.17%
R squared	0.00%	4.17%	5.59%
Number of observations	4,044	4,044	4,044

Note: Probit regression. Coefficients reported are marginal effects at the mean of other covariates, multiplied by 100. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are double-clustered at the level of lead lenders of the pre-crisis lending syndicate. A borrower is classified as borrowing from its pre-crisis lender if at least one lead lender of its post-crisis lending syndicate was a lead lender of its last pre-period syndicate. The crisis exposure of a firm's pre-crisis lender is computed as the weighted average of the relative drop in lending between 2004-2008 and 2008-10 of each lender in the firm's last pre-crisis lending syndicate, weighted by the loan share of each lender. A firm is classified as having high sales if it reports sales over the median. A firm has an existing loan covering the crisis if the maturity of its last pre-crisis loan is after December 2010. Pre-crisis loan terms include: spread, size, whether it was secured by collateral, and whether there were multiple lead lenders or two or less participants in its syndicate. The sample is restricted to U.S. non-financial firms that list the reason for borrowing as "working capital" or "corporate purposes."

Table 3: First stage estimates

these shocks are orthogonal to the corporate loan portfolio of banks. Nevertheless, I support this assumption in four different ways.

First of all, the evidence presented in section 2.4 directly goes against the idea that bad lenders were matched with bad borrowers. If that were the case, the graph would be *downward* sloping: borrowers coming from the most affected lenders would be of lower quality and find it *more difficult* to form a new relationship. Second, I run a regression at the level of the borrower-lender pair and compare a specification including firm fixed effects, which absorb any unobservable characteristics of borrower quality and demand, to OLS estimates with a full set of borrower controls. Table 10 in the Appendix shows that the two coefficients on pre-crisis lender's health are virtually identical. This comparison suggests that this bank health measure is indeed orthogonal to unobserved borrower characteristics driving post-crisis loan demand. Third, Table 11 in the Appendix shows that the sample is relatively well balanced on firm observable characteristics. Finally, the results of estimation are robust to using three other measures of banks exposure to the crisis that have been used as instruments in the literature, as I show in Section 5.4. Overall, these results are consistent with the finding of Chodorow-Reich (2014) that bank-level shocks following the financial crisis are orthogonal to unobservable borrower characteristics in this market.

5.3 Second Stage: Formation of New Relationships

Firms that saw their relationship ended have the possibility of trying to form a new relationship with a new lender b' . However, this lender knows only ν_1^f and lends only if there is positive expected surplus, conditional on its information:

$$\mathbb{E}(s) = \nu_1^f + \mathcal{W}\mathbb{E}[\nu_2^f | \mathcal{I}_{b'}] + x^f \mu + \mu_0 + \delta^{b'} \beta$$

where $\mathbb{E}[\nu_2^f | \mathcal{I}_{b'}] = -\lambda\left(\frac{\delta^{b'} \beta + x^f \mu + \nu_1^f}{\mathcal{W}}\right)$. The function $\lambda(\cdot)$ is the inverse Mills ratio, i.e. $\lambda(z) = \frac{\phi(z)}{1 - \Phi(z)}$.

The identity of the new lender is unrecorded if no new loan is made, I thus need to estimate δ^b as part of the second stage. I allow for some level of heterogeneity across firms along a vector of observables z^f . I assume that $\delta^b \beta = \delta^{MIN} \beta + z^f \gamma$. The first term $\delta^{MIN} \beta$ represents the no search friction benchmark, in which firms approach the least affected lender for a new loan. The second term $z^f \gamma$ represents possible deviation from this benchmark, with γ to be estimated.³¹ The vector z^f includes indicators for whether the firm is public, received multiple loans in the pre-crisis period, and is in the manufacturing sector, as well as an intercept.

Denote the cutoff rule used to accept new borrowers by $\nu_1^f \geq \nu^{*f}(\delta^b, x^f, z^f)$. The probability that a firm borrows from a new lender, conditional on seeing its existing relationship ended, is thus given by:

$$\begin{aligned} \mathbb{P}(\text{borrow from a new lender}) &= \mathbb{P}(\nu_1^f \geq \nu^{*f}(\delta^b, x^f, z^f) | \nu^f \leq \bar{\nu}(\delta^b, x^f)) \\ &= \int_{\nu^f \leq -\delta^b \beta - x^f \mu} \Phi \left(\frac{1}{\mathcal{W}} (\nu^f - \nu^{*f}(\delta^b)) \right) \frac{\phi(\nu^f)}{1 - P_1^f} d\nu^f \end{aligned}$$

The information gap \mathcal{W} as well as γ is estimated via non-linear least squares regression, i.e.

$$(\hat{\mathcal{W}}, \hat{\gamma}) = \operatorname{argmin} \sum_f \left[\mathbb{1}(f \text{ borrows from new lender}) - \mathbb{P}(\nu_1^f \geq \nu^{*f}(\delta^b, x^f, z^f) | \nu^f \leq \bar{\nu}(\delta^b, x^f)) \right]^2 \quad (11)$$

5.4 Second Stage Estimation Results

The estimated information gap between lenders is 15.13% and detailed estimation results are presented in Table 4. This positive gap implies that new lenders indeed know less than existing lenders about their borrowers. The moderate magnitude of \mathcal{W} is unsurprising: recall that it measures information *relative* to the econometrician, and \mathcal{W} is scaled by the standard deviation of the unobservable ν^f . A moderate magnitude reflects the fact that there is a large amount of

³¹For instance, Boualam (2015) emphasizes search frictions inherent to credit reallocation.

Parameters	Interpretation	Estimated value	90% confidence interval
\mathcal{W}	Information gap	15.13%	[8.31%,38.57%]
γ	<i>Shifters of $\delta^b \beta = \delta^{MIN} \beta + z^f \gamma$</i>		
	Public	0.00	[-0.03,0.02]
	Multiple pre-crisis loans	-0.02	[-0.04,0.00]
	Manufacturing	-0.01	[-0.02,0.02]
<i>Cross-sectional mean of $z^f \gamma$</i>		0.31	
<i>Cross-sectional standard deviation of $z^f \gamma$</i>		0.14	

Note: Coefficients are estimated via non-linear least squares on the subsample of firms that did not renew their relationship after the crisis. Confidence intervals are bootstrapped to account for the fact that the first stage is estimated. A borrower is classified as renewing its relationship if at least one lead lender of its post-crisis lending syndicate was a lead lender of its last pre-crisis syndicate. The sample is restricted to U.S. non-financial firms that list the reason for borrowing as "working capital" or "corporate purposes."

Table 4: Second stage estimation results: main specification

information that is unobservable to the econometrician but is known to all lenders, independent of the information gap. This result confirms the existence of an information hierarchy in this market, with three distinct levels of information. However, a moderate magnitude does not imply that the information gap has no effect on aggregate lending. To gauge these effects, the Section 6 conducts the appropriate counterfactual exercise.

Table 12 in the Appendix presents results for a number of alternative specifications. In particular, I reestimate the model using three different measures of bank exposure to the crisis that have been used previously in the literature. The first measure is the fraction of loan co-syndicated with Lehman Brothers before the crisis, as introduced in Ivashina and Scharfstein (2010). The idea behind this measure is that lenders with joint obligations with Lehman Brothers had to step in after its collapse, reducing their ability to finance new loans. The second measure is the loading of bank stock price on the mortgage-backed security ABX index as introduced in Chodorow-Reich (2014). The last measure is the bank ratio of real estate charge-offs to assets following the crisis computed with balance sheet data, in the spirit of Murfin (2012) and Chodorow-Reich (2014).

These different measures from a variety of data sources help to alleviate two concerns: (i) that the main bank health measure is contaminated by borrower characteristics, and (ii) that bank health is mis-measured in the first stage so that ν^f also captures unobservable lender characteristics. I reestimate the model using each of these three measures instead and find the estimated information gap is relatively stable. Compared to a baseline of $\mathcal{W} = 15.13\%$, the model using Lehman exposure estimates it to be 17.94%, the one using real estate chargeoffs 12.81% and the one using the ABX loading a somehow smaller value of 8.67%. These results confirm the existence of an information gap between lenders, as well as the existence of substantial information common to all lenders but unobservable to the econometrician.

As a last validation of the empirical strategy, I reestimate the model after deliberately including fewer control variables in the vector x^f . In particular, I drop the characteristics of the firm’s pre-crisis loan, as this information is not included in typical firm-level datasets. Given that the information gap measures how informed new lenders are *relative to the econometrician*, the information gap should fall in this specification. Indeed, the estimated information drops by ten percent, from 15.13% to 13.52%. Intuitively, the omitted controls are now part of the common information ν_1^f shared by all lenders. The information of all lenders therefore overlaps more and the information gap is smaller. Interestingly, this also suggests that failing to include relevant independent information in x^f only *underestimates* the information gap.

5.5 Information Sharing within Lending Syndicate

An important question is: how easily can lenders communicate information about borrowers within a lending syndicate? In fact, if lenders could freely communicate their private information to others, loan syndication would be a potential solution for eliminating the information gap. In this section, I develop a new method to test this hypothesis relying on the estimation framework described above by using the composition of the firm’s lending syndicate. In particular, I redefine how to classify firms that borrow from a new lender. In the baseline model, a firm is defined as borrowing

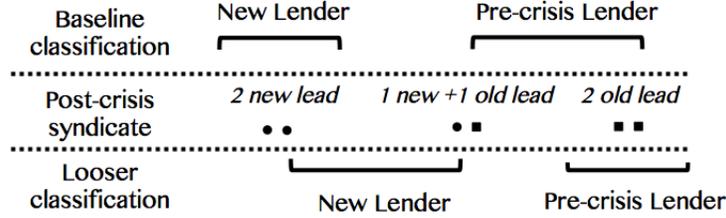


Figure 8: Test for information sharing within lending syndicate

from a new lender if none of the lead lenders of the post-crisis syndicate were lead lender in the pre-crisis syndicate. In the looser classification, one new lead lender is enough to be classified as a new lender. Estimating the model with the looser classification leads to a large increase in the estimated information gap, from 15.13% to 22.78%. This large increase is direct evidence that information sharing is difficult even for lenders within the same lending syndicate.

To see this, consider the schematic representation of the test depicted in Figure 8. There are three types of lending syndicates after the crisis: syndicates with two new lead lenders, syndicates with one new and one old, and syndicates with two old lead lenders. In the looser classification, the first two types are grouped together as "new lender," while in the baseline classification the last two are grouped together as "pre-crisis lender." The information gap measures how informed the "pre-crisis lender" group is relative to the "new lender" group.

If information flows freely between the new and old lender within a group, the middle type of syndicates with one old lead and one new lead would know as much as the third type with two old lead lenders. Grouping this middle type with syndicates consisting only of new lead lenders should thus *reduce* the relative gap in information measured by \mathcal{W} in the looser classification. This reduction would be due to the fact that the "new lender" group is now relatively more informed. However, I find the opposite pattern: the estimated information gap increases dramatically. This suggests that the information of syndicates consisting of an old and a new lender is in fact closer to that of consisting of two new lenders. This evidence suggests that soft information about borrowers is difficult to credibly communicate across lenders, consistent with the existence of an information

gap.³²

6 Counterfactuals

6.1 Aggregate Effects of the Information Gap

The model estimates can answer the following counterfactual question: how many loans were not made after the crisis because of the information gap and imperfect reallocation? Table 5 shows the effects on aggregate lending of assuming that all lenders have the same information, i.e. assuming that $\mathcal{W} = 0$.

More precisely, in this counterfactual, new lenders apply the same lending rule used by informed lenders, estimated in the first stage. Formally, the counterfactual probability that firm f borrows in the second stage is given by:

$$\mathbb{P}_{\mathcal{W}=0}(f \text{ borrows from a new lender}) = \mathbb{P}(\nu^f \geq \bar{\nu}(\delta^{b'}, x^f) | \nu^f \leq \bar{\nu}(\delta^b, x^f)) \quad (12)$$

where the full information cutoff $\bar{\nu}$ is estimated in the first stage.

Counterfactual aggregate lending is significantly higher: the lending rate increases from 0.65 to 0.68. This increase comes through a sizable improvement in credit reallocation: if all lenders had the same information, the probability of forming a new relationship would increase by 30%, or about 1.5 percentage points. In order to translate this share into a dollar estimate, I use the median post-crisis loan size in the data. In the main specification, this results in about \$14 billion in loans not made after the crisis because of the information gap. For comparison, Table 5 also reports the estimates resulting from using the 25th percentile instead. This table also shows the estimates resulting from using different measures of bank crisis exposure. The specification using Lehman exposure and real estate charge-offs yields aggregate effects of \$19 and \$10 billion respectively,

³²This evidence also echoes the results of Ivashina (2009), who shows that participants in a lending syndicate demand a higher spread in response to the private information of a lead bank.

while using ABX loading implies a smaller effect.

The key reason behind using the identification strategy introduced in this paper is the idea that information ν_1^f common to all lenders but unobservable to the econometrician leads to bias when estimating the information gap. To make this point clear, I estimate a naive model that ignores this common information. As in described in Section 4, this naive model assumes that the distribution of firms that see their relationship ended is independent of pre-crisis lender exposure, i.e. $\nu_1^f \perp \delta^b$. More precisely,

$$\mathbb{P}_{\text{naive}}(f \text{ borrows from a new lender}) = \mathbb{P}(\nu_1^f \geq \nu^*(\delta^b, \delta^{b'}, x^f | \mathcal{W})) \quad (13)$$

where ν^* is the lending rule that new lenders use in the presence of an information gap.

Table 6 shows that the naive model dramatically overestimates the information gap and its effects: both \mathcal{W} and the counterfactual increase on aggregate lending are three times larger. This large bias is consistent with the previous finding that common information ν_1 is quantitatively important.

6.2 Decomposing the Drop in Lending after the Crisis

Effects of the information gap from the previous section can be compared to reduced-form estimates of the total effects of relationship stickiness, following the approach of Chodorow-Reich (2014) or Jimenez et al. (2014) for instance. This approach quantifies the effects of bank idiosyncratic shocks on firms' ability to borrow. However, it cannot isolate the contribution of a specific reallocation friction such as the information gap. Nevertheless, this approach yields an estimate of an *upper bound* for the effects of this information gap, computed independently from the empirical strategy introduced in this paper.

To compute the effects of all reallocation frictions, the first step is to run the following firm

	Post-crisis outcome		
	Lending rate	Increase in lending(\$bn)	
		using median post-crisis loan size	using 25th percentile
Data	0.65	-	-
<i>Counterfactuals (no information gap)</i>			
Main model	0.68	14	8
90% confidence interval	[0.65,0.70]	[2.3,54]	[1.3,34]
95% confidence interval	[0.65,0.72]	[1.5,76]	[0.9,44]
<i>Other specifications</i>			
Lehman Exposure	0.69	19	11
ABX loading	0.66	3	2
RE Chargeoffs	0.67	10	6

Note: The lending rate is computed as $2 \times$ share of firms with a loan in 2004-08 that received a new loan in 2008-10. In the main model, the crisis exposure of a firm's pre-crisis lender is defined as the weighted average of the relative fall in lending between 2004-2008 and 2008-10 of each lender in the firm's last pre-crisis lending syndicate, weighted by the loan share of each lender. Confidence intervals are bootstrapped to account for the fact that the first stage is estimated. Lehman exposure is defined as the fraction of loan co-syndicated with Lehman Brothers before the crisis, ABX loading is the loading of bank stock price on the mortgage-backed security ABX index and real estate chargeoffs is the ratio of real estate charge-offs to assets following the crisis. These last three bank variables can be found on Gabriel Chodorow-Reich's website. For each model, the counterfactual lending rate is computed by assuming that the information gap \mathcal{W} is equal to zero. The median post-crisis loan size is computed from the sample of firms that received a loan in the pre-crisis period. The sample is restricted to U.S. non-financial firms that list the reason for borrowing as "working capital" or "corporate purposes."

Table 5: Aggregate effects of information gap

	Main model	Naive model
Information gap	15.13%	56.65%
Counterfactuals		
<i>Lending rate</i>	0.68	0.74
<i>Increase in lending (\$ bn)</i>	14	44

Note: The lending rate is computed as 2× share of firms with a loan in 2004-08 that received a new loan in 2008-10. The naive model ignores the fact that only a subset of firms reaches the second stage. For each model, the counterfactual lending rate is computed by assuming that the information gap \mathcal{W} is equal to zero. The median post-crisis loan size used to measured the increase in dollar lending is computed from the sample of firms that received a loan in the pre-crisis period. The sample is restricted to U.S. non-financial firms that list the reason for borrowing as "working capital" or "corporate purposes."

Table 6: Estimates from naive model ignoring common information ν_1

level regression:

$$P(\text{borrow}) = \underbrace{\gamma * \delta^b}_{\text{Pre-crisis lender's health}} + \text{Firm controls} + \epsilon$$

where the dependent variable is an indicator for whether the firm receives a new loan after the crisis *from any lender*. The parameter of interest is γ the coefficient on the firm's pre-crisis lender's health. In a world without reallocation frictions, firms can costlessly find a new lender to replace their existing lender if needed and this coefficient is zero. The final step is to use the estimate $\hat{\gamma}$ to compute the counterfactual with no reallocation friction:

$$P(\text{borrow})^{CF} = \hat{P}(\text{borrow}) + \hat{\gamma} * (\delta_{MIN} - \delta^b)$$

where $\hat{P}(\text{borrow})$ are the fitted values from the first step regression and δ_{MIN} is the exposure of the least affected lender. Concretely, this counterfactual corresponds to the case in which all firms had a relationship with the least affected lender, therefore implying that there is no reallocation problem. The key difference with the previous counterfactual is that this includes all reallocation frictions, and not just the information gap.

Table 7 displays the results from this counterfactual exercise, while Table 14 in the Appendix

Post-crisis outcome	Baseline	Counterfactual	
		No reallocation friction	No information gap
Lending rate	0.65	0.72	0.68
Increase in lending (\$ bn)		34	14

Note: The lending rate is computed as $2\times$ share of firms with a loan in 2004-08 that received a new loan in 2008-10. In the counterfactual with no reallocation friction, the counterfactual lending rate is computed by assuming that all firms borrowed before the crisis from the least affected lender. In the counterfactual with no information gap, the counterfactual lending rate is computed by assuming that the information gap \mathcal{W} is equal to zero. The median post-crisis loan size used to measure the increase in dollar lending is computed from the sample of firms that received a loan in the pre-crisis period. The sample is restricted to U.S. non-financial firms that list the reason for borrowing as "working capital" or "corporate purposes."

Table 7: The aggregate effects of imperfect credit reallocation

presents the estimates of the first step OLS regression. With no reallocation friction and perfect credit reallocation, the lending rate would increase from 0.65 to 0.72, corresponding to a \$34 billion increase in loans being made after the crisis. This evidence suggests that, while aggregate shocks explain most of the drop in lending after the crisis, the information gap is the key friction driving imperfect credit reallocation. Quantitatively, aggregate shocks to the financial and real sectors account for about 80% of the drop. The information gap explains another 10%, while other reallocation frictions explain the remaining 10%.

6.3 Targeted Interventions in the Banking Sector

This section considers a different counterfactual exercise related to policy. In particular, during a crisis policy makers often implement *targeted* interventions aimed at providing public support for the most affected lenders. For instance, the Capital Purchase Program was part of the Troubled Asset Relief Program (TARP) authorized by Congress in the fall of 2008. It provided over \$200 billion in equity injections to many large U.S. financial institutions. Institutions receiving CPP funds were either among the most affected by the crisis according to my measure, or purchased

some of the most affected banks. A key question is how these targeted interventions impacted aggregate lending.³³

I conduct the following counterfactual mimicking this type of intervention: I consider the quartile of firms that have a relationship with the most affected lenders and increase the health of these lenders counterfactually. As a benchmark, I compare the predictions of the model with an information gap to the reduced-form model introduced in the previous section:

$$P(\text{borrow}) = \gamma * \text{Pre-crisis lender's health} + \text{Firm controls} + \epsilon$$

Figure 9 presents the results, and Table 15 in the Appendix includes the details. The x-axis measures the magnitude of the intervention and denotes the counterfactual decrease in the worst lenders' exposure. The y-axis measures the impact of the intervention and the increase in aggregate lending, in billions of dollars. The key message is that interventions targeting the weakest lenders have unintended consequences. In particular, they have negative side effects on credit reallocation that reduces their effectiveness.

Intuitively, the model that explicitly incorporates the information gap predicts a smaller impact of interventions compared to the reduced-form model because it can account for these equilibrium effects. More precisely, direct support for the weakest lenders has two distinct effects. The first is a positive *bank-level* effect: the share of firms able to renew their relationship with these lenders increases. However, this intervention hurts the borrowers that are not able to renew their relationship: it dilutes the positive signal that comes from the selection effect. There is therefore a second, negative effect on credit reallocation. In fact, Figure 9 shows that for interventions that are not forceful enough, the second effect can dominate. This logic is related to the models of Uhlig (2010) and Malherbe (2014), who study adverse selection in very different settings.

Figure 10 summarizes the economic forces at play. Consider what happens to borrowers with

³³Admittedly, these interventions also often have multiple objectives, such as preventing bank runs or domino effects.

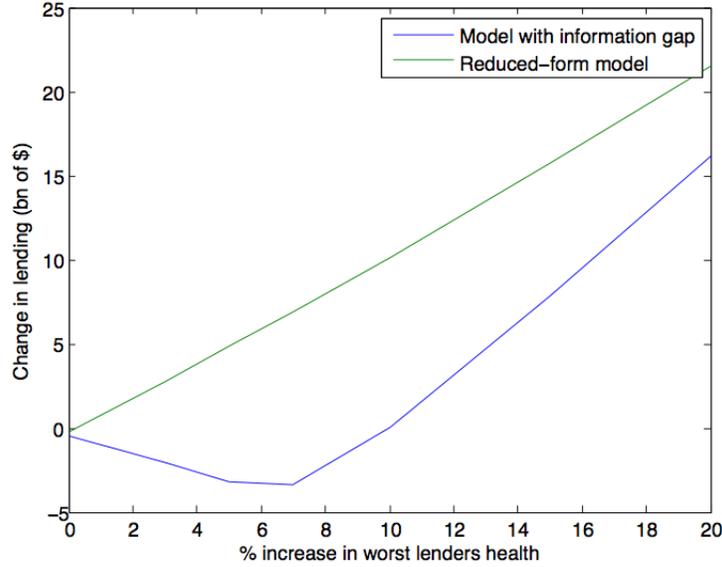


Figure 9: Unintended consequences of targeted interventions

an existing relationship to a specific lender b . The left panel represents the laissez-faire equilibrium before the intervention and mirrors the analysis of Section 3. Firms are distributed on the x-y plane, with their true type $\nu^f = \nu_1^f + \mathcal{W}\nu_2^f$ on the y-axis and the common information ν_1^f on the x-axis. Firms above $\bar{\nu}(\delta^b)$ are able to renew their relationship with lender b in the first stage. However, only firms with ν_1^f above ν^* are able to form a new relationship with lender b' in the second stage. The information gap implies that new lenders adopt stricter lending rules ($\nu^* > \bar{\nu}(\delta^{b'})$) and there is therefore an underfunding region.

The right panel of Figure 10 shows that an intervention supporting lender b has two effects. It first pushes down $\bar{\nu}(\delta^b)$ and increases the share of firms that are able to renew their relationship. However, part of this increase is purely *redistributive*: some of these firms would have been able to find a new lender absent the intervention. The increase in aggregate lending is thus smaller than what the increase in relationship renewal would suggest at face value.³⁴ In addition, there is a second equilibrium effect: the cutoff ν^* used by the new lender moves to the right. Indeed, the intervention dilutes the positive signal received by borrowers that saw their relationship ended

³⁴In fact, in the limit case in which there is no information gap, a targeted intervention has only redistributive effects (not shown).

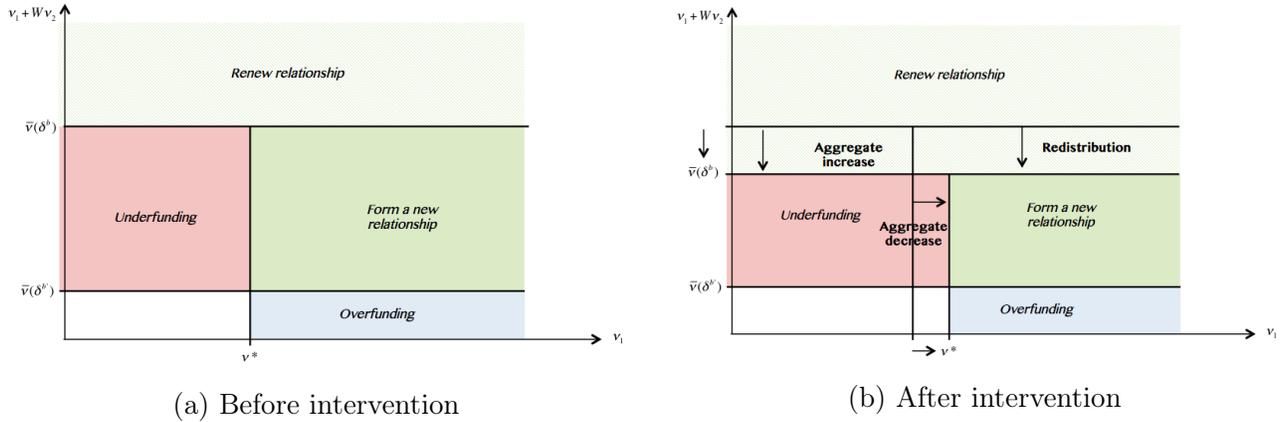


Figure 10: Impact of targeted intervention: aggregate effect vs. redistribution

and increases the stigma that they face. This force reduces the number of new relationships and limits the positive impact of the intervention on aggregate lending.

6.4 Fostering Credit Reallocation

The results of the previous section open the following broad question: could institutions aimed at fostering credit reallocation replace some of the interventions supporting the weakest banks? To answer this question, I conduct two additional counterfactual exercises.

First, I find that improvements in firm transparency can have large effects. I run an extended specification that estimates the information gap separately for private and public firms. Consistent with the idea that private firms are less transparent to outsider financiers, I find that their information gap is 30% larger relative to public firms. Moreover, this cross-sectional heterogeneity provides an additional support that the measure \mathcal{W} accurately reflects informational frictions.

In a counterfactual in which all firms are as transparent as public firms, aggregate lending would be \$4 billion higher. This figure implies that the difference in transparency between private and public firms accounts alone for a third of the total effect of the information gap. A number of theoretical works have argued in favor of information sharing and transparency in lending markets, see for example Japelli and Pagano (2006) for a survey. My quantitative findings suggest that

policies aimed at improving firm transparency can mitigate the drop in lending during a crisis, even if they do not fully eliminate the information gap. The main channel is to facilitate the movement of borrowers across lenders.

Second, I study the effects of a public intervention aimed at directly fostering credit reallocation. More precisely, I consider subsidizing loans made to new borrowers whose existing relationship has ended. The Funding for Lending Scheme (FLS) implemented in the U.K. in 2012 had a similar flavor by making public support conditional on lending, except that I focus here on loans made to new clients of a bank. I introduce a subsidy $s > 0$ that increases the lending capacity of the new lender that a firm approaches in the second stage.³⁵ Formally, the subsidy is equivalent to reducing the crisis exposure of the new lender proportionally:

$$\delta^{b'SUBSIDY} = \delta^{b'}(1 - s)$$

Figure 11 illustrates the effects of such a policy on aggregate lending. As opposed to interventions targeting the weakest lenders, this type of intervention unambiguously increase aggregate lending. It promotes the movement of borrowers by counteracting the stigma associated with leaving a relationship. The benefits of this approach are that it aids the relatively healthier lenders and makes public support conditional on lending.

This type of policy relates to the debate on whether the government should lend directly to financially constrained firms. A common view is that if these constraints are due to informational frictions, there is no reason the government should be able to improve on the market outcome. The type of interventions considered above represents a middle ground: lending and screening are still performed by financial institutions. Nevertheless, the optimal size of the subsidy is an interesting open question. The welfare trade-off is to counteract stigma without inducing overfunding by banks, and I leave this question for future research.

³⁵The subsidy is not restricted to a direct monetary transfer; it could be implemented by relaxing the collateral accepted for short-term funding (like in the FLS) or lower capital requirements on these loans for example.

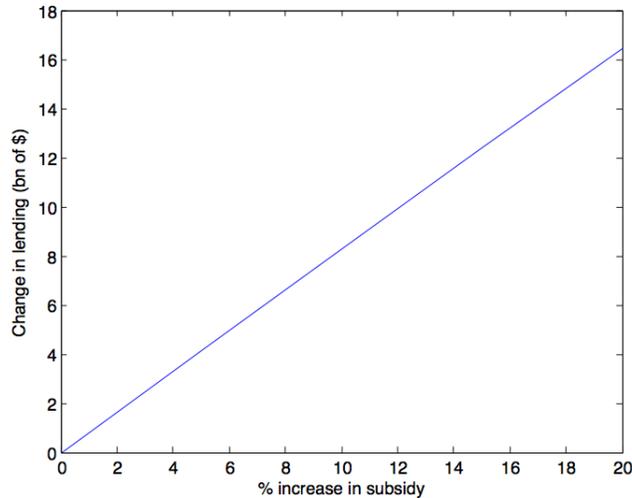


Figure 11: Subsidizing lenders to accept new borrowers

7 Conclusion

This paper studies the effects of an informational friction in credit reallocation. Lenders have different information about borrowers and this information gap makes switching lenders difficult. In turn, this friction implies that bank-specific shocks have aggregate effects as borrowers can only imperfectly reallocate across lenders. I introduce a new approach to credibly identify the information gap and apply it to the U.S. syndicated loan market.

Beyond simply showing the existence of this informational friction, I quantify its effect on aggregate lending and credit reallocation after the financial crisis. I estimate \$15 billion more in loans would have been made in the counterfactual in which the information gap is zero. This aggregate figure is due to a sizable improvement in credit reallocation at the firm level: the probability of forming a new relationship would be 30% higher if all lenders shared the same information.

I find that there are three distinct levels of information among agents in this market. A firm's existing lender knows more than its potential new lenders, but all lenders know more than what is observable to the econometrician. I argue that this information hierarchy implies that reduced-form estimates of the information gap are biased and show that naive information models dramatically

overestimate the effects of this friction on lending.

I also show the implications of imperfect credit reallocation for policy interventions targeting the weakest banks. These interventions have unintended consequences on credit reallocation that reduce their effectiveness. When it comes to limiting a drop in aggregate lending, policies aimed at fostering credit reallocation have the potential to replace some of the direct support received by troubled banks. Optimal policy design requires quantitative models that can account for equilibrium effects in credit reallocation, in the line of the one developed in this paper.

Finally, the methodology is fairly general and could potentially be applied to other settings where relationships are important. Possible examples include employment relationships, relationships with a firm's large customers or suppliers, or with professionals such as lawyers or accountants.

8 References

Becker, Bos and Roszbach, "Bad Times, Good Credit", Working Paper, 2015

Berger and Udell, "Relationship Lending and Lines of Credit in Small Firm Finance", Journal of Business, 1995

Berg, Saunders and Steffen, "The Total Costs of Corporate Borrowing in the Loan Market: Don't Ignore the Fees", Journal of Finance, forthcoming.

Botsch and Vanasco , "Relationship Lending: Do Banks Learn?", Working Paper, 2015

Boualam, "Bank Lending and Relationship Capital", Working paper, 2015.

Chaney, Thesmar and Sraer, "The Collateral Channel", American Economic Review, 2012

Chodorow-Reich, "The Employment Effects of Credit Market Disruptions: Firm-Level Evidence from the 2008-09 Financial Crisis", Quarterly Journal of Economics, 2014

Degryse and Van Cayseele, "Relationship Lending Within a Bank-Based System: Evidence from European Small Business Data", Journal of Financial Intermediation, 2000

Detragiache, Garella, and Guiso, "Multiple versus Single Banking Relationships: Theory and Evidence", Journal of Finance, 2000

David, Hopenhayn, Venkateswaran, "Information, Misallocation and Aggregate Productivity", Quarterly Journal of Economics, forthcoming.

Dickstein and Morales, "What do Exporters Know?", working paper, 2015.

Einav, Jenkins and Levin, "Contract Pricing in Consumer Credit Markets", Econometrica, 2012

Einav, Finkelstein and Schrimpf, "Optimal Mandates and the Welfare Cost of Asymmetric Information: Evidence from the UK Annuity Market", Econometrica, 2010

Gibbons and Katz, "Layoffs and Lemons", Journal of Labor Economics, 1991

Greenstone, Mas and Nguyen, "Do Credit Market Shocks affect the Real Economy? Quasi-Experimental Evidence from the Great Recession and 'Normal' Economic Times", Working Paper, 2014

Hanson, Kashyap and Stein, "A Macroprudential Approach to Financial Regulation", Journal of Economic Perspective, 2011.

Heckman, "Sample Selection as a Specification Error", Econometrica, 1979

Ivashina, "Asymmetric Information Effects on Loan Spreads", Journal of Financial Economics, 2009

Ivashina and Scharfstein, "Bank Lending during the Financial Crisis of 2008," Journal of Financial Economics, 2010

Jappelli and Pagano , "Information Sharing in Credit Markets: A Survey" , published in "The Economics of Consumer Credit: European Experience and Lessons from the U.S", edited by G. Bertola, R. Disney, and C. Grant. Cambridge: The MIT Press, 2006

Jimenez, Mian, Peydro, and Saurina, "The Real Effects Of The Bank Lending Channel", Working Paper, 2014

Keys, Mukherjee, Seru and Vig, "Did Securitization Lead to Lax Screening? Evidence From Subprime Loans", Quarterly Journal of Economics, 2010

Kahn, "Asymmetric Information between Employers", American Economic Journal: Applied, 2013

Khwaja and Mian, "Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market," American Economic Review, 2008

Liberti and Mian, "Estimating the Effect of Hierarchies on Information Use", Review of Financial Studies, 2009

Hombert and Matray, "The Real Effects of Lending Relationships on Innovative Firms and Inventor Mobility", Working Paper, 2015

Malherbe, "Self-fulfilling Liquidity Dry-ups", Journal of Finance, 2014

Mian, "Distance Constraints: The Limits of Foreign Lending in Poor Economies" Journal of Finance, 2006

Murfin, "The Supply-Side Determinants of Loan Contract Strictness", The Journal of Finance, 2012

Peek and Rosengren, "Collateral Damage: Effects of the Japanese Bank Crisis on Real Activity in the United States," American Economic Review, 2000

Petersen and Rajan, "The Benefits of Lending Relationships: Evidence From Small Business Data", Journal of Finance, 1994

Rajan, "Insiders and Outsiders: The Choice Between Informed and Arm's Length Debt", Journal of Finance, 1992

Schonene, "Lending Relationships and Information Rents: Do Banks Exploit Their Information Advantages?", Review of Financial Studies, 2010

Rajan, Seru and Vig, "The Failure of Models That Predict Failure: Distance, Incentives and Defaults", Journal of Financial Economics, 2014

Sharpe, "Asymmetric Information, Bank Lending and Implicit Contracts: A Stylized Model of Customer Relationships", Journal of Finance, 1990

- Shlain, "Do Firms and the Market Believe in the Spare Tire Hypothesis?", working paper, 2015.
- Srinivasan, "Long Run Relationships in Banking", in "Foundations and Trends in Finance" Vol. 8: No. 2, 2014
- Stroebel, "Asymmetric Information about Collateral Values", Journal of Finance, 2015
- Stroebel and Kurlat, "Testing for Information Asymmetries in Real Estate Markets", Review of Financial Studies, 2015
- Uhlig, "A Model of a Systemic Bank Run", Journal of Monetary Economics, 2010

A Appendix

A.1 Additional Tables

	Outcome: Firm borrows from a new lender, conditional on not borrowing from its pre-crisis lender			
	(1)	OLS (2)	(3)	IV (4)
Pre-crisis lender exposure	0.52 (0.47)	0.62 (0.41)	0.69** (0.35)	3.26** (1.29)
Firm characteristics	No	Yes	Yes	Yes
Pre-crisis loan characteristics	No	No	Yes	Yes
N	3,188	3,188	3,188	3,188
R-squared	0.01%	0.70%	1.57%	0.26%

Note: OLS regression. Coefficients reported are multiplied by 100. $*p < 0.10$; $**p < 0.05$; $***p < 0.01$. Standard errors are double-clustered at the level of lead lenders of the pre-crisis lending syndicate. A borrower is classified as borrowing from its pre-crisis lender if at least one lead lender of its post-crisis lending syndicate was a lead lender of its last pre-period syndicate. The crisis exposure of a firm's pre-crisis lender is computed as the weighted average of the relative fall in lending between 2004-2008 and 2010-08 of each lender in the firm's last pre-crisis lending syndicate, weighted by the loan share of each lender. Firm characteristics include: public ownership, high sales, manufacturing sector, received multiple pre-crisis loans, has a pre-crisis loan that extends throughout the post-crisis period. Pre-crisis loan characteristics include: spread, size, whether it was secured by collateral and whether there was multiple lead lenders or two or less participants in its syndicate. Instruments used for bank exposure: fraction of loans co-syndicated with Lehman, stock price loading on ABX index, real estate charge-offs over assets, as reported on Gabriel Chodorow-Reich's website. The sample is restricted to U.S. non-financial firms which list the reason for borrowing as "working capital" or "corporate purposes".

Table 8: The selection effect: OLS regressions

	Dependent variable:		
	(1) Log post-crisis loan size	(2) Post-crisis loan spread	(3) Post-crisis loan collateralized
New lender dummy	-0.26*** (0.06)	23.7* (13.95)	0.03 (0.04)
Pre-crisis lender exposure	Yes	Yes	Yes
Post-crisis lender exposure	Yes	Yes	Yes
Borrower characteristics	Yes	Yes	Yes
Last pre-crisis loan terms	Yes	Yes	Yes
R squared	0.37	0.22	0.32
Number of observations	741	679	741

Note: OLS regression. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are double-clustered at the level of lead lenders of the pre-crisis lending syndicate. Dependent variables are loans terms of the first new loan received in the post-crisis period. A borrower is classified as borrowing from its pre-crisis lender if at least one lead lender of its post-crisis lending syndicate was a lead lender of its last pre-period syndicate. Other borrowers receiving a loan after the crisis are classified as borrowing from a new lender. The crisis exposure of a lending syndicate is computed as the weighted average of the relative fall in lending between 2004-2008 and 2010-08 of each lender in the lending syndicate, weighted by the loan share of each lender. Borrower characteristics include: public ownership, high sales, manufacturing sector, received multiple pre-crisis loans, has a pre-crisis loan that extends throughout the post-crisis period. Pre-crisis loan terms include: spread, size, whether it was secured by collateral and whether there was multiple lead lenders or two or less participants in its syndicate. The sample is restricted to U.S. non-financial firms which list the reason for borrowing as "working capital" or "corporate purposes" and receive a loan both in the pre-crisis and post-crisis period.

Table 9: Loan terms received by new lenders: OLS regressions

	Outcome: % change in loan size after the crisis	
	(1) FE	(2) OLS
Pre-crisis lender's exposure	-2.28*** (0.12)	-2.35*** (0.45)
Borrower fixed effects	Yes	No
Firm characteristics	No	Yes
Pre-crisis loan terms	No	Yes
R squared	7.67%	10.31%
N. obs.	4,649	4,649

Note: Column (1): borrower FE regression; column (2): OLS regression. Coefficients reported are multiplied by 100. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. In the OLS specification, standard errors are double-clustered at the level of lead lenders of the pre-crisis lending syndicate. Pre-crisis and post-crisis loan size are recovered from the total loan amount across the syndicate and the loan share of each lender in the syndicate. Lender's crisis exposure is computed as the relative fall in lending between 2004-2008 and 2010-08 at this lender. Firm characteristics include: public ownership, high sales, manufacturing sector, received multiple pre-crisis loans, has a pre-crisis loan that extends throughout the post-crisis period. Pre-crisis loan characteristics include: spread, size, whether it was secured by collateral and whether there was multiple lead lenders or two or less participants in its syndicate. The sample is restricted to U.S. non-financial firms which list the reason for borrowing as "working capital" or "corporate purposes".

Table 10: First stage identification: comparing FE and OLS loan-level regressions

Outcome: Pre-crisis lender's exposure

Firm characteristics

Public	-0.03
High sales	-0.01
Existing loan covers the crisis	-0.03
Multiple pre-crisis loans	-0.03
Manufacturing	0.11**

Last pre-crisis loan terms

Pre-crisis loan spread	0.00***
Pre-crisis loan size	0.00
Pre-crisis loan maturity	0.00***
Secured by collateral	0.13**
Two or less participants	0.10

R squared	6.96%
-----------	-------

Number of observations	4,044
------------------------	-------

Note: OLS regression. Standard errors are double-clustered at the level of lead lenders of the pre-crisis lending syndicate. The crisis exposure of a firm's pre-crisis lender is computed as the weighted average of the relative fall in lending between 2004-2008 and 2010-08 of each lender in the firm's last pre-crisis lending syndicate, weighted by the loan share of each lender. The sample is restricted to U.S. non-financial firms which list the reason for borrowing as "working capital" or "corporate purposes".

Table 11: First stage identification: balancing on covariates

Parameters	Main model	Lehman exposure	ABX loading	Chargeoffs
Information gap \mathcal{W}	15.13%	17.94%	8.67 %	12.81 %
<i>Shifters of $\delta^b \beta = \delta^{MIN} \beta + z^f \gamma$</i>				
Public	0.00	-0.01	0.00	0.00
Multiple pre-crisis loans	-0.02	-0.02	-0.02	-0.02
Manufacturing	-0.01	0.00	0.0	0.00
<i>Mean of $z^f \gamma$</i>	0.31	0.31	0.23	0.19
<i>Standard deviation of $z^f \gamma$</i>	0.14	0.17	0.08	0.01

Note: Coefficients are estimated via non-linear least squares on the subsample of firms which did not renew their relationship after the crisis. A borrower is classified as renewing its relationship if at least one lead lender of its post-crisis lending syndicate was a lead lender of its last pre-crisis syndicate. In the main model, the crisis exposure of a firm's pre-crisis lender is defined as the weighted average of the relative fall in lending between 2004-2008 and 2010-08 of each lender in the firm's last pre-crisis lending syndicate, weighted by the loan share of each lender. Lehman exposure is defined as the fraction of loan co-syndicated with Lehman Brothers before the crisis, ABX loading is the loading of bank stock price on the mortgage-backed security ABX index and real estate chargeoffs is the ratio of real estate charge-offs to assets following the crisis. These last three bank variables can be found on Gabriel Chodorow-Reich's website. The sample is restricted to U.S. non-financial firms which list the reason for borrowing as 'working capital' or 'corporate purposes'.

Table 12: Second stage estimation results: robustness

Parameters	Main model	Fewer controls	New classification
Information gap \mathcal{W}	15.13%	13.52%	22.78 %
<i>Shifters of $\delta^b \beta = \delta^{MIN} \beta + z^f \gamma$</i>			
Public	0.00	0.00	0.09
Multiple pre-crisis loans	-0.02	0.02	-0.03
Manufacturing	-0.01	0.00	-0.02
<hr/>			
<i>Mean of $z^f \gamma$</i>	0.31	0.33	0.67
<i>Standard deviation of $z^f \gamma$</i>	0.14	0.16	0.25

Note: Coefficients are estimated via non-linear least squares on the subsample of firms which did not renew their relationship after the crisis. In the main model and the specification with fewer controls, a borrower is classified as borrowing from a new lender if no lead lenders of its post-crisis lending syndicate were a lead lender of its last pre-crisis syndicate. In the “new classification” specification, a borrower is classified as borrowing from a new lender if at least one lead lenders of its post-crisis lending syndicate was not a lead lender of its last pre-crisis syndicate. In the all specifications, the crisis exposure of a firm’s pre-crisis lender is defined as the weighted average of the relative fall in lending between 2004-2008 and 2010-08 of each lender in the firm’s last pre-crisis lending syndicate, weighted by the loan share of each lender. The sample is restricted to U.S. non-financial firms which list the reason for borrowing as ‘working capital’ or ‘corporate purposes’.

Table 13: Second stage estimates: alternative specifications

Outcome: Borrow from any lender			
Pre-crisis lender's exposure	-3.08*** (1.13)	-2.49*** (0.87)	-1.90*** (0.73)
Borrower characteristics	No	Yes	Yes
Pre-crisis loan terms	No	No	Yes
Mean of dep. variable	25.05%	25.05%	25.05%
R squared	0.50%	4.19%	5.44%
Number of obs.	4,044	4,044	4,044

Note: OLS regressions. Coefficients reported are multiplied by 100. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are double-clustered at the level of lead lenders of the pre-crisis lending syndicate. The crisis exposure of a firm's pre-crisis lender is computed as the weighted average of the relative fall in lending between 2004-2008 and 2010-08 of each lender in the firm's last pre-crisis lending syndicate, weighted by the loan share of each lender. Firm characteristics include: public ownership, high sales, manufacturing sector, received multiple pre-crisis loans, has a pre-crisis loan that extends throughout the post-crisis period. Pre-crisis loan characteristics include: spread, size, whether it was secured by collateral and whether there was multiple lead lenders or two or less participants in its syndicate. The sample is restricted to U.S. non-financial firms which list the reason for borrowing as "working capital" or "corporate purposes".

Table 14: No reallocation friction counterfactual: first step OLS regression

% fall in worst lenders crisis exposure	Lending rate			
	Information gap model			Reduced-form model
	Previous lender	New lender	Total	Total
0% (Baseline)	54.74	13.02	64.84	64.84
5%	56.22	10.51	63.33	65.92
10%	57.82	9.45	64.86	67.11
15%	59.56	9.45	66.60	68.36
20%	61.42	9.45	68.46	69.65

Note: The lending rate is computed as $2\times$ share of firms with a loan in 2004-08 that receive a new loan in 2008-10. A borrower is classified as borrowing from its pre-crisis lender if at least one lead lender of its post-crisis lending syndicate was a lead lender of its last pre-period syndicate. Other borrowers receiving a loan after the crisis are classified as borrowing from a new lender. The crisis exposure of a firm's pre-crisis lender is computed as the weighted average of the relative fall in lending between 2004-2008 and 2010-08 of each lender in the firm's last pre-crisis lending syndicate, weighted by the loan share of each lender. The sample is restricted to U.S. non-financial firms which list the reason for borrowing as "working capital" or "corporate purposes".

Table 15: Targeted policy interventions: counterfactual aggregate lending

A.2 Omitted Proofs

Proof of Lemma 1:

$$\begin{aligned}
\frac{\partial \mathbb{E}[s|\nu_1]}{\partial \nu_1} &= \int_{\nu_2 \leq \frac{\bar{\nu} - \nu_1}{\mathcal{W}}} \left(\frac{\partial}{\partial \nu_1} s(\nu_1 + \mathcal{W}\nu_2, \mu_0, x, r') + s(\nu_1 + \mathcal{W}\nu_2, \mu_0, x, r') \frac{f_2\left(\frac{\bar{\nu} - \nu_1}{\mathcal{W}}\right)}{F_2\left(\frac{\bar{\nu} - \nu_1}{\mathcal{W}}\right)} \right) \frac{dF_2(\nu_2)}{F_2\left(\frac{\bar{\nu} - \nu_1}{\mathcal{W}}\right)} \\
&\quad - s(\bar{\nu}, \mu_0, x, r') \frac{f_2\left(\frac{\bar{\nu} - \nu_1}{\mathcal{W}}\right)}{F_2\left(\frac{\bar{\nu} - \nu_1}{\mathcal{W}}\right)} \\
&= \int_{\nu_2 \leq \frac{\bar{\nu} - \nu_1}{\mathcal{W}}} \frac{\partial}{\partial \nu_1} s(\nu_1 + \mathcal{W}\nu_2, \mu_0, x, r') \frac{dF_2(\nu_2)}{F_2\left(\frac{\bar{\nu} - \nu_1}{\mathcal{W}}\right)} \\
&\quad + \frac{f_2\left(\frac{\bar{\nu} - \nu_1}{\mathcal{W}}\right)}{F_2\left(\frac{\bar{\nu} - \nu_1}{\mathcal{W}}\right)} \int_{\nu_2 \leq \frac{\bar{\nu} - \nu_1}{\mathcal{W}}} (s(\nu_1 + \mathcal{W}\nu_2, \mu_0, x, r') - s(\bar{\nu}, \mu_0, x, r')) \frac{dF_2(\nu_2)}{F_2\left(\frac{\bar{\nu} - \nu_1}{\mathcal{W}}\right)} \\
&\geq \int_{\nu_2 \leq \frac{\bar{\nu} - \nu_1}{\mathcal{W}}} \frac{\partial}{\partial \nu_1} s(\nu_1 + \mathcal{W}\nu_2, \mu_0, x, r') \frac{dF_2(\nu_2)}{F_2\left(\frac{\bar{\nu} - \nu_1}{\mathcal{W}}\right)} \\
&\quad + \frac{f_2\left(\frac{\bar{\nu} - \nu_1}{\mathcal{W}}\right)}{F_2\left(\frac{\bar{\nu} - \nu_1}{\mathcal{W}}\right)} \int_{\nu_2 \leq \frac{\bar{\nu} - \nu_1}{\mathcal{W}}} \frac{\partial}{\partial \nu_1} s(\nu_1 + \mathcal{W}\nu_2, \mu_0, x, r') (\nu_1 + \mathcal{W}\nu_2 - \bar{\nu}) \frac{dF_2(\nu_2)}{F_2\left(\frac{\bar{\nu} - \nu_1}{\mathcal{W}}\right)} \\
&= \int_{\nu_2 \leq \frac{\bar{\nu} - \nu_1}{\mathcal{W}}} \frac{\partial}{\partial \nu_1} s(\nu_1 + \mathcal{W}\nu_2, \mu_0, x, r') \left(1 + \frac{f_2\left(\frac{\bar{\nu} - \nu_1}{\mathcal{W}}\right)}{F_2\left(\frac{\bar{\nu} - \nu_1}{\mathcal{W}}\right)} (\nu_1 + \mathcal{W}\nu_2 - \bar{\nu}) \right) \frac{dF_2(\nu_2)}{F_2\left(\frac{\bar{\nu} - \nu_1}{\mathcal{W}}\right)} \\
&> \int_{\nu_2 \leq \frac{\bar{\nu} - \nu_1}{\mathcal{W}}} k \left(1 + \frac{f_2\left(\frac{\bar{\nu} - \nu_1}{\mathcal{W}}\right)}{F_2\left(\frac{\bar{\nu} - \nu_1}{\mathcal{W}}\right)} (\nu_1 + \mathcal{W}\nu_2 - \bar{\nu}) \right) \frac{dF_2(\nu_2)}{F_2\left(\frac{\bar{\nu} - \nu_1}{\mathcal{W}}\right)} \\
&> 0
\end{aligned}$$

The third step follows from the concavity of s (TC3(i)). The fifth step follows from (TC3(ii)).

The last step follows from the log-concavity of F_2 (TC1).

Proof of Proposition 4: Define the full information cutoff ν_{FI} implicitly by $s(\nu_{FI}, \mu_0, x, r') = 0$. Moreover, ν^* is defined implicitly by $\int_{\nu_2 \leq \frac{\bar{\nu} - \nu_1}{\mathcal{W}}} s(\nu^* + \mathcal{W}\nu_2, \mu_0, x, r') \frac{dF_2(\nu_2)}{F_2(\frac{\bar{\nu} - \nu_1}{\mathcal{W}})} = 0$. Therefore:

$$s(\nu_{FI}, \mu_0, x, r') = 0 \tag{14}$$

$$= \int_{\nu_2 \leq \frac{\bar{\nu} - \nu_1}{\mathcal{W}}} s(\nu^* + \mathcal{W}\nu_2, \mu_0, x, r') \frac{dF_2(\nu_2)}{F_2(\frac{\bar{\nu} - \nu_1}{\mathcal{W}})} \tag{15}$$

$$\leq s(\nu^* + \mathcal{W} \int_{\nu_2 \leq \frac{\bar{\nu} - \nu_1}{\mathcal{W}}} \nu_2 \frac{dF_2(\nu_2)}{F_2(\frac{\bar{\nu} - \nu_1}{\mathcal{W}})}, \mu_0, x, r') \tag{16}$$

$$< s(\nu^*, \mu_0, x, r') \tag{17}$$

Therefore, $\nu_{FI} < \nu^*$. The third step follows from TC3(i) and Jensen's inequality.