Estimating Informational Frictions in Sticky Relationships

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Abstract

This paper introduces a novel empirical approach to estimate the effects of an informational friction limiting the reallocation of credit after a shock to banks. Because lenders rely on private information when deciding which relationship to end, borrowers looking for a new lender are adversely selected. I show how to identify private information separately from information common to all lenders, but unobservable to the econometrician, by using bank shocks within a discrete-choice model of relationships. Applying this approach to the U.S. corporate loan market during the recent crisis, this informational friction can explain 10% of the decrease in lending.

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

JEL codes: G21, D82, L14

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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 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 private ("soft") information about their borrowers that is unobservable to other lenders.[3] The information gap represents the informational advantage that stems from relationship lending. The main contribution of this paper is to provide a novel empirical strategy to deliver the first direct estimate of the magnitude of the information gap as well as of its effect on lending.

The key identification challenge is that, empirically, *private* information is difficult to disentangle from *common* information that all lenders can observe but that the econometrician cannot. This paper shows how to use shocks to banks to identify lenders' private information separately from information common to all lenders. I demonstrate this idea by applying it to study the U.S. corporate loan market during the recent crisis, following Chodorow-Reich (2014). I find that lenders have significant private information and that $14 billion new loans were not made following the crisis because of this informational friction. The estimates can also be used to assess the effectiveness of various credit market policies and interventions.

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.[4]

This channel makes clear why shocks to banks' ability to lend can be useful in identifiying

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

[2]For 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.

[3]See 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.

[4]Importantly, this cherry-picking 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 of borrowers with lenders but not the share of borrowers receiving a loan.

the information friction. In fact, it implies an "inference hypothesis": borrowers leaving the most affected lenders are less adversely selected, as described in Dell'Ariccia and Marquez (2004). Intuitively, these lenders cannot continue lending even to relatively good borrowers. Therefore, this inference hypothesis implies that 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.[5] 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 and use a lender's exposure to this shock to measure its ability to lend in the corporate loan market. 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.[6]

However, this evidence does not solve the main identification challenge of isolating private information. In fact, the same reduced-form correlation would emerge if there were only common information that all lenders could observe but that the econometrician could not. In that case, new lenders would not learn any additional information from a relationship being ended. They simply would prefer lending to better borrowers, which are mechanically more likely to come from more affected lenders, i.e. there is selection on common information.

The key idea to address this challenge is to exploit a comparison with the sample of borrowers who renewed their relationships. This comparison is useful because relationship renewal reflects how informed lenders lend to borrowers, and introduces a benchmark against which new lenders can be compared. Models with and without private information make different predictions on the *joint* pattern of renewal and creation of relationships.

To this end, I introduce a two-stage discrete-choice model of firm borrowing. In the first stage, firms try to renew their relationship with their existing lender. Each lender faces a shock impacting its ability to lend. If a borrower fails to receive a new loan from its existing lender, it can turn to new lenders in the second stage. The main 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.

The first stage can be estimated by regressing the probability that a firm renews its relationship with its existing lender on firm and lender characteristics. The identifying assumption is that the shock to banks' ability to lend are unrelated to the unobservable characteristics of its borrowers.[7]

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

[6] An equivalent finding in labor markets can be found in Gibbons and Katz (1997).

[7] Any such credit supply shock would do. In the application, I follow Chodorow-Reich (2014) to construct a variety of shocks to banks active in the syndicated loan market that appear to be orthogonal to borrowers' characteristics.

The information gap is estimated in the second stage, using the subsample of firms that saw their relationship ended in the first stage. In line with the "inference hypothesis" above, this stage estimates how the probability that a firm finds a new lender depends on the shock faced by its previous lender. Unlike a purely reduced-form approach, it is possible to control for the mechanical selection on common information of firms who did not renew their relationship. Indeed, the first stage precisely characterizes how renewal depends on shocks to a firm's previous lender. 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.[8]

In the application to the U.S. syndicated loan market, I find that the information gap significantly reduced firms' access to credit during the crisis. 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 $14 billion of loans would have been made if all lenders had had the same information. 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: estimates of the information gap and its aggregate effects would be three times larger than in the benchmark model.

The model estimates can also be used to study a number of policy counterfactuals. In an attempt to prevent breakdowns in lending markets in times of crisis, policy makers often devote substantial resources to support weak lenders.[9] However, when the main friction behind relationship stickiness is the information gap, these interventions have unintended consequences. In equilibrium, 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. A policy experiment suggests that this equilibrium effect can be sizable. I therefore provide a couple other counterfactuals about fostering credit reallocation without directly supporting the weakest lenders.

This paper is organized as follows. To make the methodology concrete, Section 2 uses the case of the U.S. syndicated corporate loan market to describe data requirements, and the measurement of relationship and banks shocks, as well as to explain in detail the identification challenge. Section 3 develops the empirical model of firm borrowing and reallocation in which lenders have different

[8]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.

[9]The Capital Purchase Program implemented in 2008 is an example of such public support. It was part of the Trouble 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.

information about borrowers. Section 4 explains how this model can be used to address the identification challenge of isolating private information. Section 5 describes the estimation procedure and the results for the U.S. corporate loan market. Sections 6 contains all counterfactual exercises. Section 7 concludes.

1.1 Related Work

This paper relates to the works estimating the effect of credit supply shocks. It is closest to Chodorow-Reich (2014), given that the empirical application is based on his framework for measuring relationships and bank shocks in the U.S. syndicated loan market after the financial crisis.[10] Relative to this literature, I focus on the explicit mechanism by which bank-specific shocks impact firm borrowing and isolate the effects of informational frictions. This paper offers a direct empirical test of the model of Dell'Ariccia and Marquez (2004).

I also contribute to the growing literature on estimating informational frictions. For instance, Stroebel (2015) and Stroebel and Kurlat (2014) have provided clean evidence for differences in information on the same side of the market, respectively for mortgage lenders and homeowners. They show how more informed agents outperform others. My focus on aggregate lending and market breakdown is complementary to these papers. Machiavello and Morjaria (2015) show how reputation concerns shape relationships with exporters, while I focus on the information gap. Moreover, a number of works have shown that soft information matters for lending, including Mian (2006), Liberti and Mian (2009), Hertzberg, Liberti and Paravisini (2011), Botsch and Vanasco (2015), Rajan, Seru and Vig (2014), Sutherland (2016) and Keys et al. (2010).

A key contribution of this paper is to quantify the effect of informational frictions, beyond simply testing for their existence. I share this objective with a growing body of work in the economic literature, including David, Hopenhayn and Venkateswaran (2015), Dickstein and Morales (2015), Einav, Finkelstein and Levin (2010) or Einav, Finkelstein and Schrimpf (2010).

This focus complements the banking 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) or Berger and Udell (1995). Finally, 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 being laid off face shorter unemployment and receive higher post-displacement wages.

[10]See also Peek and Rosengren (2000), Khwaja and Mian (2008) and Jimenez et al. (2014), among others.

2 The Empirics of Relationships: the U.S. Corporate Loan Market

How should one think of relationships and informational frictions in an empirical setting? To make the empirical strategy concrete, this section illustrates the key ideas through the case of the U.S. corporate loan market. I focus on three main points: data requirements, the empirical question, and the identification challenge. The following sections will adopt a more general approach.

2.1 Data Requirements

The key data requirement is to be able to trace relationships between borrowers and lenders. For this purpose, it is necessary to have loan-level data describing who borrowed from which bank at each point in time. In particular, balance sheet data on borrowers or banks are not sufficient on their own.

The data for the application studied in this paper come 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 Rosengreen 2000, Chaney et al. 2012) and firm employment (Chodorow-Reich 2014, Greenstone, Mas and Nguyen 2014), as well as innovation activity (Matray and Hombert, 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 accounted for about 50% of C&I lending with a maturity of more than one day and 60% with a maturity of more than one year. These 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.

A significant body of work has shown that relationships matter in this market. Idiosyncratic shocks to banks have negative effects on borrowers through a variety of channels: issuance of new loans (Ivashina and Scharfstein, 2010), employment (Chodorow-Reich, 2014), loan pricing (Santos, 2011) or loan contract strictness (Murfin, 2012). This is reassuring given the relatively large size of these firms. Nevertheless, there are reasons to believe that estimates of information frictions from DealScan would constitute a lower bound compared to the average smaller, more opaque firm.[11]

[11] All of these papers contain details on how variables are constructed, as well as institutional details. See also

In fact, the empirical application is taken from Chodorow-Reich (2014). Like him, I will focus on how banks' exposure to the recent real estate crisis has affected lending to borrowers in the corporate market. The time frame centers on the bankruptcy of Lehman Brothers in September 2008. I divide the sample between a pre-crisis period spanning January 2004 to August 2008 and the crisis period spanning October 2008 to December 2010. I include only loans made to non-financial, American firms and that were used for financing the operations of the firm.[12]

This sample is attractive because 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.[13] 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. In general, any application should have a substantial fraction of borrowers who depend on banking relationships.

2.2 The Question: The Impact of Bank Shocks

How do bank shocks impact credit markets? A key idea is that sticky relationships make credit markets more vulnerable. If a friction prevents some borrowers of a distressed bank from switching to a new, relatively healthier lender, even idiosyncratic bank shocks can have aggregate effects. The goal of this paper is to estimate the aggregate effects of an informational switching friction: the information gap across banks.

Like many other lending markets, the syndicated loan market suffered an unprecedented collapse after the financial crisis. Figure 1 shows that the issuance of new loans was cut in half in the sample, from an average of about $200 billion of new loans per quarter before the crisis to only $100 billion afterwards. An important feature of this market is that this collapse occurred at the *extensive margin of credit*. In fact, loan size remained stable and it was a sharp decrease in the number of firms receiving new loans that depressed lending volume after the crisis.

To study this drop in the extensive margin of credit, I focus on firms with an existing loan in a pre-crisis period spanning January 2004 to August 2008. The question is: How many of these firms obtained a new loan in the crisis period spanning October 2008 to December 2010? If they did, from whom did they borrow? Did they renew their existing relationship, or did they find a new

Roberts and Sufi (2009) for issues of misclassification in DealScan.

[12]That is when the purpose of the loan is declared as "working capital" or "corporate purposes" as opposed to M&A activity or debt restructuring.

[13]Only about half of firms in my sample are in the Compustat database.

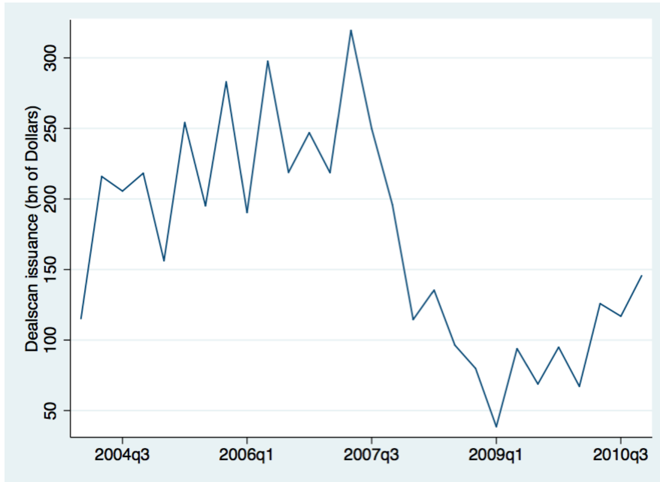


Figure 1 – Aggregate corporate issuance in DealScan (in 2008 U.S.$): 2004–2010

Year t	% firms with new loan by $t+2$	Renew	New lender
2004	42.58%	37.55%	5.03%
2008	24.63%	20.88%	3.75%
2010	36.23%	31.01%	5.22%

Note: 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

lender and form a new relationship? This distinction is key for the empirical strategy developed in this paper.[14]

Table 1 displays the decrease in lending over this period. The share of firms obtaining a new loan fell drastically after September 2008, to almost half its level in normal times.[15] Changes in loan terms are shown in Table 7 in the Appendix.

The prevalence of banking relationships is an important aspect of this market. In theory, 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

[14] The pre-crisis time length is chosen to match the typical maturity of loans before the crisis, which was just less than four years. The crisis time length is chosen to be two years because firms typically sign a new loan two years before their existing loan expires.

[15] Lending 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 received a new loan or a modification of a existing loan granting extra funds.

are valuable as lenders acquire private information about borrowers and how to efficiently adjust loan terms. This comparative advantage suggests that lending relationships are "sticky" and that forming new relationships is difficult.

Loan-level data allows the tracing of relationships, and in particular the ability to distinguish between firms that renew an existing relationship and firms that form a new relationship. In the DealScan data, I make this distinction by comparing the syndicate of the last pre-crisis loan received by a firm to that of its first new crisis loan (if any). In the main specification, 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 A.3 shows the effect of adopting a different classification.

The last two columns of Table 1 reveal how sticky lending relationships are in this market. The share of firms forming a new relationship is strikingly small at 3.75%, that is only about of fifth of the share firms renewing their existing relationship. This fact can be taken as a first piece of evidence that forming new banking relationships is difficult. Table 1 clearly illustrates the precise question this paper seek to answer: How many firms were not able to form a new relationship because potential new lenders know less than existing lenders? In other words, how much larger than 3.75% would the share of firms finding a new lender be if all banks had the same information? This counterfactual represents the aggregate effect of this information friction, via imperfect credit reallocation.

Note that this question focuses on the *extensive* margin of lending, firms' access to credit, and most of the paper relegates loan terms to the background. Although in general, data on loan terms are informative about information frictions, there are three specific reasons for this choice in this particular application. First, in terms of welfare loss, market breakdown is typically thought to have more devastating effects than higher interest rates or stricter covenants. Second, few firms switch lenders in my sample, which causes the analysis of loan terms offered to new borrowers to lack statistical power. Finally, loan terms are not only affected by informational frictions, but also by the distribution of bargaining power between borrower and lender. Conceptually, this is a complex issue. For example, one can expect new borrowers to pay a higher interest rate because new lenders are less informed. On the other hand, because relationships are sticky going forward, new lenders have incentives to offer low rates in an attempt to lock-in borrowers, as suggested by the literature on switching costs (Farell and Klemperer, 2007). While there are a number of applications for which the first and second points can be addressed, this last point requires a clear identification strategy to control for relative bargaining power. However, the empirical model of lending I develop in this paper can be estimated for any distribution of bargaining power.

2.3 Using Bank Shocks to Estimate 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 in the course of this relationship private information that is unknown to other lenders. I dub this difference in information across lenders the *information gap*.[16]

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 "cherry-picking" 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.

Where in the data can one start to look for evidence of this friction? The key idea is to exploit bank shocks, i.e. cross-sectional variation in banks' propensity to lend. Indeed, an important implication is an *inference hypothesis*. As new lenders learn something from a relationship being ended, 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 inference hypothesis corresponds to the following empirical prediction: conditional on having its previous relationship ended, the probability that a firm borrows from a new lender *increases* with the size of the shock faced by its previous lender.

This prediction can be tested directly in the data and only requires bank-specific supply shocks. In principle, many types of shocks are sufficient, whether they are truly bank-specific, such as a run on a few banks, or result from differential exposure to an aggregate shock, like the real estate crisis in this application. The only requirement is that these are *supply* shocks that are orthogonal to unobservable borrower quality and demand. These supply shocks are input to the empirical strategy. In this sense, this paper relies on the same exogenous cross-sectional variation in bank health as the empirical literature on banking relationships.

At first glance, there is evidence for this inference hypothesis in the U.S. corporate loan market during the crisis. I follow the construction of bank shocks in Chodorow-Reich (2014), who meticulously argues that these are valid supply shocks in that particular setting. The main measure of lenders' exposure to the crisis is defined 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

[16] Sharpe (1990), Rajan (1992), Detragiache et al. (2000) or Dell'Ariccia and Marquez (2004) are examples of theoretical papers studying the impact of the information gap on firms.

of loans made in the 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 asymmetrical time window between the two periods. Moreover, because these loans are syndicated across multiple lenders, I weight each element in the numerator and the denominator by the loan share of that particular lender:[17]

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

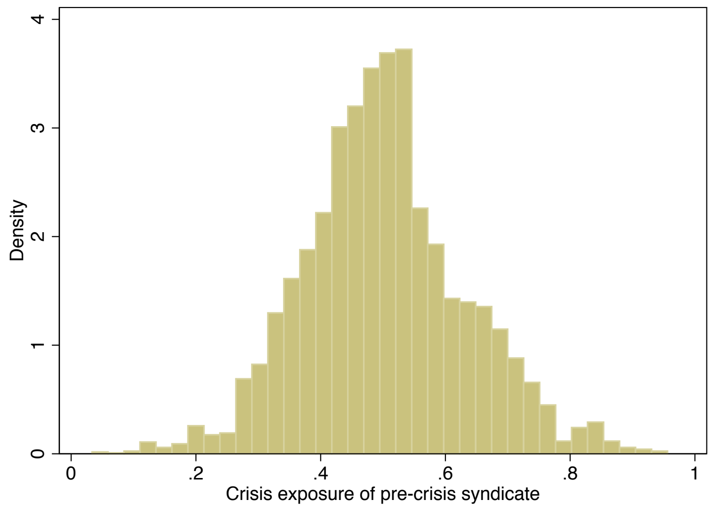
A larger δ^l implies that fewer loans were made during the crisis and indicates a more affected lender; a constant loan supply at the bank level would result in a δ^l of zero. Because syndicated loans are made by multiple lenders, I transform this lender-level measure into a firm-level measure by exploiting 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 these lender 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:

$$\delta^{s^f} = \Sigma_{l \in s^f} \omega^{l,f} \delta^l \tag{2}$$

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. Section 5 considers other measures of bank shocks, including exposure to Lehman Brothers, real estate chargeoffs, or stock price correlation with the ABX mortgage-backed securities index. Finally, for ease of exposition, in the remainder of the paper I will often refer to a syndicate as a "bank" or a "lender" and write δ^b instead δ^s, even though it is understood that firms borrow from multiple lenders at once.

Consistent with the inference hypothesis, Figure 3 shows that among firms that saw their relationship ended, 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. 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

[17]Because the data on loan shares are 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 that 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 2008–2010 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

new lender.[18]

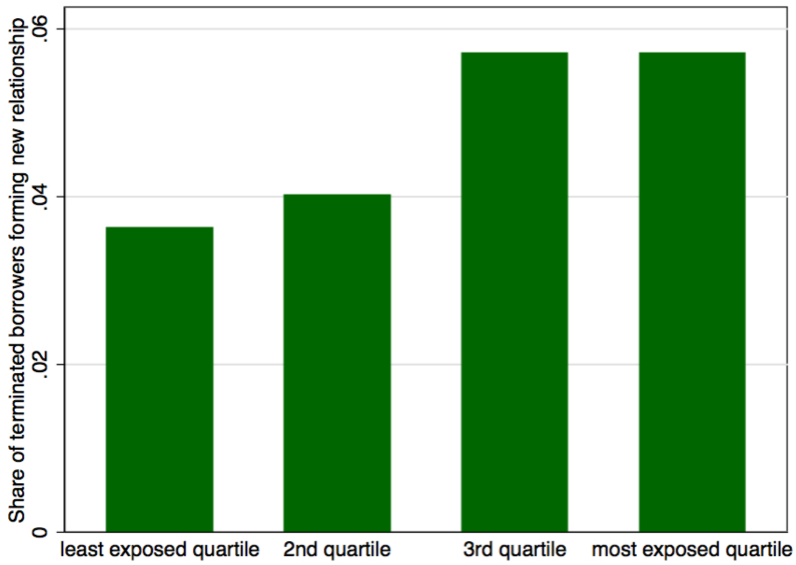
Note also that this pattern is at odds with the idea that bad borrowers were matched with less healthy lenders. Indeed, if that was the case the correlation between pre-crisis lender health and new relationships would go the other way: borrowers coming from less affected lenders would be more likely to borrow from a new lender.[19]

2.4 Empirical Challenge: Bias from Common Information

However, the reduced-form correlation in Figure 3 alone cannot identify the information gap. In fact, the same correlation would arise even if all banks had the same information, as long as some of this common information is unobservable to the econometrician. To see this, note that in this case

[18]An equivalent finding in labor markets can be found in Gibbons and Katz (1997), while Shlain (2015) provides evidence of the same pattern looking at equity issuance during the crisis.

[19]While 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 cherry-picking. 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 suggests that new borrowers are less creditworthy than repeat borrowers.



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 2008–2010 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 3 – Pre-crisis lender crisis exposure and the formation of new relationships

lenders are not *learning* anything from a relationship being ended. They simply want to lend to borrowers that are good enough. But, mechanically, there are more good borrowers leaving more affected lenders, because these lenders have to end a larger number of relationships. This channel alone, independent of private information and the information gap, could explain the correlation in Figure 3.

The existence of information common to all banks, but unobservable to the econometrician, represents the key challenge for identifying the information gap. Two channels must be disentangled: (i) new lenders learning about private information from a relationship being ended; (ii) mechanical selection on common information. Empirically, it is crucial to isolate private information because common information by itself would not lead to any inefficiency: relationships appear sticky, but with no aggregate effects.

Given that such common information is likely to exist, an important contribution of my approach is to be able to correct for this source of bias when estimating the information gap. The next section introduces a general discrete-choice model that makes this empirical challenge explicit, and Section 4 discusses in detail the strategy for isolating private information. While formal arguments are summarized there, the intuition is as follows.

The general idea is to exploit a comparison with firms that renewed their relationship. Data on relationship renewal is the missing piece because lenders are informed about borrowers when deciding whether to renew. This introduces a benchmark against which new lenders can be compared. In fact, both models, with and without private information, can explain Figure 3, but they make different predictions on the *joint* pattern of renewal and creation of relationships. Concretely, I estimate a two-stage discrete choice model, in which a first-step regression explains relationship renewal. This first stage can be used to construct the correct slope under the null of no information gap, against which the correlation in Figure 3 can be compared.

3 Empirical Model of Lending with Informational Frictions

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. This empirical framework is more general than the particular application to the U.S. corporate loan market, but can be mapped straightforwardly to the discussion of the previous section. In fact, I make frequent references to this setting in order to make the approach more concrete.

The framework takes existing relationships as given and aims to explain the pattern of lending after a shock to banks. 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 relationship data alone.

3.1 Setup

Consider a firm f with an existing relationship with lender b. After a shock to banks, the firm has a new project that requires financing (or an older project that requires new funds) and can ask for a new loan. The firm type, possibly different from its past type, is characterized by $\{x^f, \nu^f\}$.

- *Firm observables x^f:* This term includes all the controls available to the econometrician. In the DealScan sample, this includes 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, and whether it covered the crisis period, as well as whether the firm had multiple pre-crisis loans.

- *Firm unobservable type ν^f:* This term includes all firm characteristics that are unobservable to the econometrician. In other words, it corresponds to the residual in a regression framework. However, lenders have varying degrees of information about this ν^f. This information gap is the source of the friction that this paper wants to estimate.

To make this *information hierarchy* transparent, I decompose the firm type as follows:

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

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

1. ν_1^f is *common information*, observed by all lenders
2. ν_2^f is *private information* of the firm's previous lender
3. The econometrician can observe neither ν_1^f nor ν_2^f

The main parameter of interest is the *information gap* $\mathcal{W}$ that represents the weight on the previous lender private information.[20] Intuitively, there is an informational hierarchy and three

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

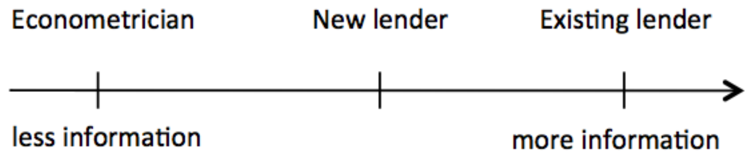


Figure 4 – Information hierarchy

levels of information, as depicted in Figure 4. At one extreme is the firm's previous 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's previous lender and its potential new lenders.[21]

Note the broad interpretation of the firm's type, defined as its propensity to receive a loan absent informational frictions. Firm characteristics can impact the surplus in lending in two ways: (i) creditworthiness, and (ii) demand for bank loans. Banks are naturally less willing to lend to firms with a poor track record or in a fledging industry. However, some "good" firms may be unwilling to borrow because they have enough financial slack, or other funding opportunities outside of the banking sector. This broad interpretation is the correct one in the context of estimating market breakdown. The question is whether firms with high enough type ν^f fail to receive a loan because of informational frictions. In terms of inefficiency it makes no difference whether a firm has a low type that reflects low creditworthiness or low demand for bank loans. In both cases, the firm would not borrow in the counterfactual of no information friction.

Besides firm type, there are two other forces that drive lending:

- *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 affected all firms. It also captures other type of aggregate shocks to lending, such as "uncertainty" shocks or events in other lending markets. This term makes sure that counterfactual lending is calibrated properly to the new period: total lending can be much lower than before the shock to the banking sector. Moreover, the fact that it captures both aggregate demand and supply shock

[21] The main specification estimates a single information gap $\mathcal{W}$ across all firms, but in principle it can vary with firm characteristics. For instance, the last section studies how $\mathcal{W}$ varies in the cross-section by comparing public and private firms.

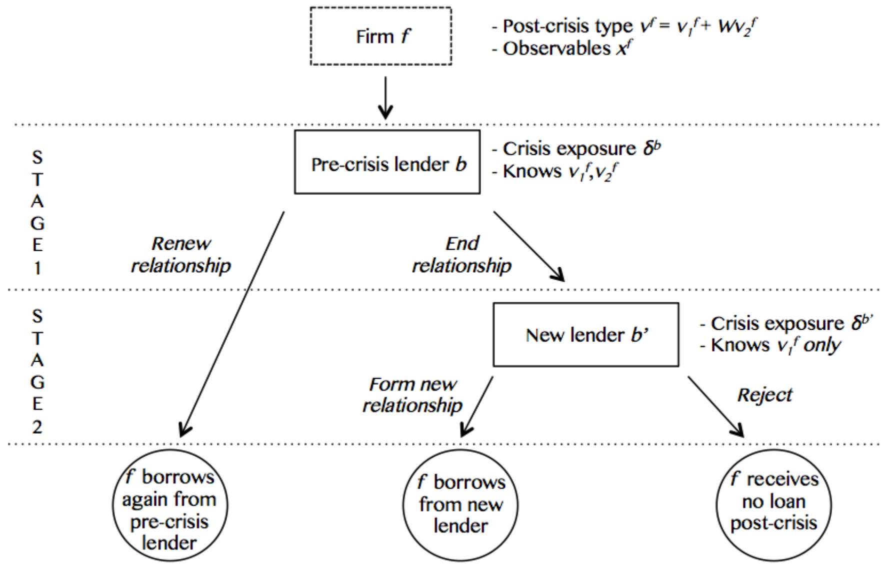


Figure 5 – The model of firm post-crisis borrowing

is not a problem as this paper focuses on a *reallocation* friction, i.e. whether bank-specific shocks have aggregate effects because of the information gap.

- *Bank-specific shock* δ^b*:* This term captures the credit reallocation problem: beyond the aggregate shock μ_0, some lenders were more affected than others. They key question is whether borrowers that saw their relationship end were able to reallocate towards new, relatively healthier lenders. In the DealScan sample, I measure δ^b with the bank's exposure to the real estate crisis measure defined in Section 2.3.

The timing of the model assumes two stages. 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 obtaining a loan from a new lender.[22] Figure 5 illustrates the setup. The next section solves for the equilibrium of each stage in turn.

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, the key moment that identifies the information gap is the selection effect: borrowers coming from

[22]Institutional details justify this timing assumption. Shopping around for 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 tend 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.

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.

3.2 Equilibrium Lending

I model lending as the outcome of a bargaining between firm and lender.[23] Lending generates a surplus $s(\nu^f, x^f, \mu_0, \delta^b)$ that depends on both firm and lender characteristics and that can be divided in the pair. A loan is made if there is positive expected surplus, i.e. lending has a positive NPV, given the information of the lender:

$$\mathbb{E}_b[s(\nu^f, x^f, \mu_0, \delta^b)] > 0$$

As emphasized above, the key friction is that not all banks b have the same information, reflected in the operator $\mathbb{E}_b$. The firm previous bank observes the complete firm type ν^f, while other lenders only observe its common component ν_1^f.[24]

Note that the model makes no prediction on how the surplus is shared in the pair, i.e. interest rate or strictness of loan terms. In fact, it is consistent with any distribution of relative bargaining powers between firm and lender. As explained in Section 2.2, this has the advantage of not confounding informational frictions with issues related to bargaining power.

In order to ensure uniqueness of equilibrium, I make the following weak technical assumptions on the distribution of firm type and the surplus function:

Technical conditions (TC)

1. F_2 is log-concave.

2. (i) $\lim_{\nu \to \nu_{min}} s(\nu, \mu_0, x, \delta) < 0$; (ii) $\lim_{\nu \to \nu_{max}} s(\nu, \mu_0, x, \delta) > 0$

3. (i) s is (weakly) concave in ν; (ii) $\partial s / \partial \nu$ is positive and uniformly bounded away from zero.

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 of trying to form a new relationship and obtaining a loan from a new, but less informed,

[23] Given the complex and dynamic nature of relationships, a bargaining model seems more realistic than a competitive pricing or auction model.

[24] As in most discrete-choice model, this lending rule is not fully microfounded. Intuitively, it is equivalent to assuming the existence of an indirect utility function in consumer choice models.

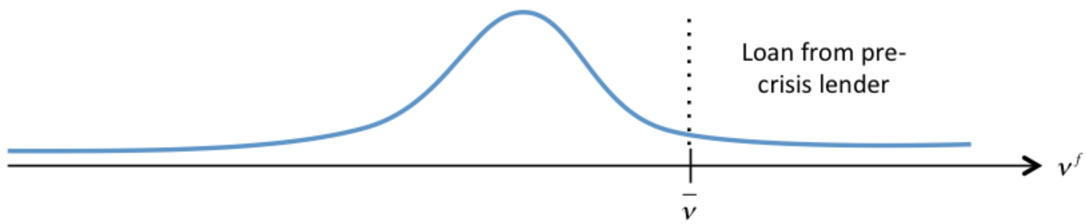


Figure 6 – Stage 1: renewing existing relationships.

lender. This section solves for the equilibrium of these two stages in turn. All omitted proofs are in the Appendix.

3.2.1 First stage: relationship renewal

First, the firm can try to renew its relationship with its existing lender and obtain a new loan. This lender knows ν^f and the loan is granted if there is a positive surplus in the pair given this information. The relationship is renewed for firms with a sufficiently high type, relative to the bank shock δ^b:

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

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

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.

This cutoff $\bar{\nu}(\mu_0, x^f, \delta^b)$ represents the *informed lender decision rule* and plays a crucial role in the identification strategy described below.

3.2.2 Second stage: new relationship formation

Firms that saw their relationship ended in stage 1 can try to form a new relationship and borrow from a new lender b'. The new lender cannot observe the full type ν^f but has two sources of information. First, it can directly observe the common information component ν_1^f. Second, leaving a relationship is a signal in itself and lets the lender make an inference about the private information component ν_2^f. In particular, the set of firms looking for a new lender is selected:

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

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

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

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:*

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

Proof: Follows from Lemma 1.

The key difference with the first stage is that the cutoff rule is different: $\nu^*(\mu_0, x^f, \delta^b, \delta^{b'})$ represents the *uninformed lender decision rule.* In general, this rule is stricter than the informed decision $\bar{\nu}$ because borrowers looking for a new lender are adversely selected.[25] Importantly, the cutoff ν^* depends on the size of the firm's previous lender shock δ^b:

Proposition 3 ***(Inference hypothesis)*****:** If $\mathcal{W} > 0$, *ν^* decreases with the firm's previous lender crisis shock 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 apply looser lending standards to borrowers that ended a relationship with the most affected lenders. This looser lending rule reflects that lenders are learning private

[25] The proof is in the Appendix. Moreover, as the information gap goes to zero, this rule converges to the informed lender cutoff $\bar{\nu}$.

information that they cannot observe directly. These borrowers are on average of higher private type ν_2^f and therefore face less stigma.

This inference hypothesis is the key empirical prediction of the information gap, and Section 4 emphasizes the challenge associated with isolating this channel. At this point, the crucial point to keep in mind is that private information affects the *lending rule* used by new lenders.

3.3 Inefficiencies and Market Breakdown

Figure 7 illustrates the effect of the information gap on lending. The x-axis represents the commonly observed component of firm's 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 was 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 green area 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 red area 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. In fact, the objective of this paper is to estimate the total effect of the information gap on lending.

4 Identifiying the Information Gap

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. This section takes a general approach while the next section applies it to the U.S. corporate loan market.

4.1 Sources of Variation

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 face different shocks

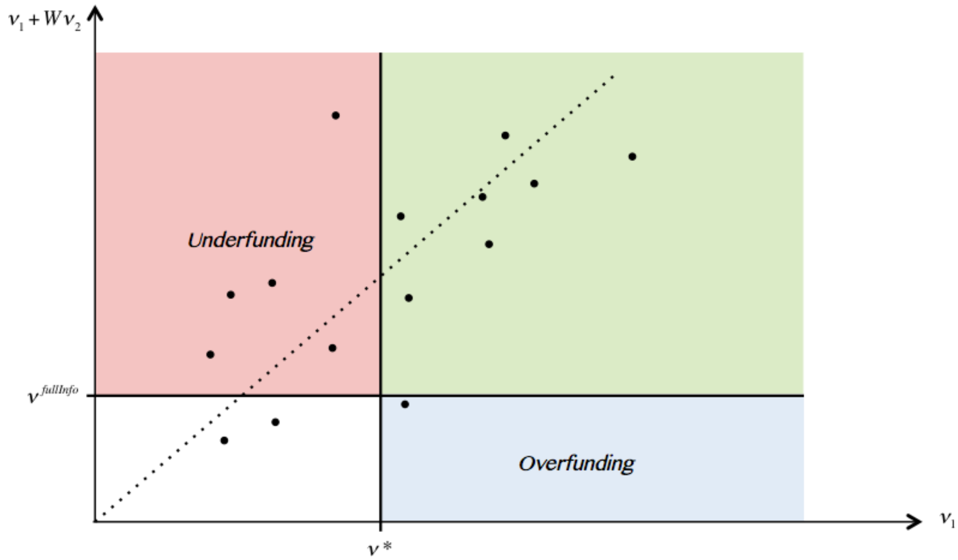


Figure 7 – The effect of the information gap on lending

to their propensity to make loans. 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 inference hypothesis summarized in Proposition 3 and described in Section 2.3 empirically in the U.S. syndicated loan market.

The idea is that, among borrowers that saw their previous relationship ended, firms coming from the most affected lenders find it easier to find a new lender. Intuitively, new lenders apply looser lending standards to borrowers that ended a relationship with the most affected lenders because they face less stigma. Formally, recall that a firm coming from lender b forms a new relationship with b' if :

$$\nu_1^f \geq \nu^*(\delta^b, \delta^{b'})$$

The key comparative statics is that the uninformed lending rule ν^* decreases with δ^b.[26] This looser lending rule reflects that lenders are learning about private information ν_2^f that they cannot observe directly. The empirical correlation between the size of the shock faced by a firm's previous lender and its probability of forming a new relationship is thus informative about the information gap.

[26]For ease of exposition, I suppress the dependence on firm observables x^f in the notation as they play no role in identifying private information.

4.2 Identification Challenge: Bias from Common Information

However, this correlation alone cannot identify the information gap, as it is also partly driven by selection on information ν_1^f common to all lenders. As the econometrician cannot directly observe lenders' information, it is not possible to separately identify lender's private information from the common information component using the reduced form correlation alone.

To see this, consider the extreme case of no private information, i.e. $\mathcal{W} = 0$. In this case, new lenders are not learning anything from a relationship being ended. Formally, they use the same lending rule as informed lender: $\nu^*(\delta^b, \delta^{b'}) = \bar{\nu}(\delta^{b'})$. There is no longer any inference: this lending is independent of the shock to the firm's previous lender δ^b. However, the sample reaching stage 2 is selected: $\nu_1^f \leq \bar{\nu}(\delta^b)$. The model equivalent of the reduced-form correlation is given by:

$$\mathbb{P}(f \text{ borrows from a new lender}) \;=\; \mathbb{P}(\nu_1^f \geq \bar{\nu}^f(\delta^{b'}) | \nu_1^f \leq \bar{\nu}(\delta^b)) \tag{7}$$

which implies a positive correlation even without private information.

This is the essence of the empirical challenge of isolating the information gap. Models with and without private information can both rationalize the positive correlation between previous lender shock and the probability of finding a new lender.

4.3 Addressing the Challenge: Exploiting First-Stage Renewal Data

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 for which they have private information.

Intuitively, if there were no information gap, the lending decision of new lenders should match the lending decision rule of informed lenders. In other words, estimating a first-stage equation implies a restriction that distinguishes between models with and without private information. These models make different predictions on the *joint* pattern of renewal and creation of relationships.

Concretely, I estimate relationship renewal as the first stage of the model. I estimate the probability that a firm renews its relationship with its previous lender as a function of the lender's shock δ^b and firm characteristics x^f.[27] In other words, the first stage estimates the *informed lender decision rule* $\bar{\nu}(x^f, \delta^b)$ that determines which firms renew their relationship:

$$\text{firm } f \text{ renews relationship with lender } b \iff \nu^f \geq \bar{\nu}(x^f, \delta^b) \tag{8}$$

[27] The notation of this section includes controls x^f for completeness.

The information gap $\mathcal{W}$ is estimated in the second stage in which firms coming from different lenders look for a new relationship. The model equivalent of the reduced-form correlation is given by:

$$\mathbb{P}(f \text{ borrows from a new lender}) = \mathbb{P}(\nu_1^f \geq \nu^*(\delta^b, \delta^{b'}, x^f, \mathcal{W}) | \nu^f \leq \bar{\nu}(x^f, \delta^b)) \quad (9)$$

where ν^* is the *uninformed lender decision rule* given information gap $\mathcal{W}$. This expression makes clear that previous lender shock δ^b is correlated with the probability of forming a new relationship through two channels:

1. Inference about private information ν_2^f: how new lenders adjust their lending rule ν^* with δ^b
2. Selection on common information ν_1^f: only the subsample with $\nu^f \leq \bar{\nu}(x^f, \delta^b)$ reaches the second stage

The benefit of having estimated the first-stage decision rule $\bar{\nu}$ is immediate: it allows to control for the bias caused by common information and estimate the information gap only from changes in the lending rule used by new lenders. In principle, the information gap can be estimated to be zero if the second channel is enough to match the reduced-form correlation observed in the data. The value of this two-step approach is that the information gap is estimated only from the variation in second stage lending probabilities that is unexplained by common information.

4.4 Discussion

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. Indeed, these forces are unlikely to vary systematically with the shock to the firm's previous lender, i.e the regressor of interest δ^b.

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 those models. A traditional selection model only accounts for information unobservable to the econometrician and cannot isolate what is private information to a subset of agents.

The first maintained assumption is that previous and new lenders would use the same lending rule (as a function of borrower and lender characteristics) if they had the same information.[28] This is likely to hold in this setting because lenders are not divided into groups of "informed" and "uninformed" banks. In fact, the same lender is informed about some borrowers, but uninformed about others. The second maintained assumption is that the distribution of borrower unobservables is common across lenders. This is the familiar assumption that δ^b represents a true supply shock, strengthen by the necessity of making a parametric assumption about this distribution. Nevertheless, as the idea behind identification does not rely on functional form, any distribution satisfying the technical conditions of Section 3 can be used. This corresponds to choosing whether the first-stage regression is a probit, logit, linear probability, or another discrete-choice model.

5 Estimation and Results

5.1 Overview

This section applies the identification strategy to the U.S. corporate loan market.

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

- 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:

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

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:

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

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

The parameters $(\mathcal{W}, \beta, \mu)$ are estimated using the two-stage discrete-choice model of firm borrowing describe in the previous section. In the first stage, I estimate the probability that a firm

[28] With possibly a different intercept to reflect fixed costs of starting a new relationship.

renews its relationship with its pre-crisis lender. In the second stage, I estimate that 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 previous lender knows the type ν^f and renews its relationship based on a linear cutoff rule:[29]

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

The probability that firm f renews his 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 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 described in Section 2.3. 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 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 fewer participants in its syndicate.

Results are presented in Table 2. The normalized marginal effect of 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 point, or about 15% of the average renewal rate. The economic and statistical significance of this measure of bank crisis exposure justifies 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.

Indentifying β. The identification assumption for the first stage is that δ^b is orthogonal to unobservable 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. Because the crisis

[29] For 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.

	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 2008–2010 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 fewer 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 2 – First stage estimates

originated in the real estate market, it is at least plausible in this particular case that these shocks are orthogonal to the corporate loan portfolio of banks. Chodorow-Reich (2014) gives a detailed discussion supporting the validity of this assumption in this particular sample. Nevertheless, I support this assumption in four different ways, replicating a number of his tests.

First of all, the evidence presented in section 2.3 goes directly 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 *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 bank's exposure to the crisis that have been used as instruments in the literature, as I show in Section 5.3. 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 a positive expected surplus, conditional on its information:

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

where $\mathbb{E}_{b'}[\nu_2^f] = -\lambda\left(\frac{\delta^b\beta + x^f\mu + \nu_1^f}{\mathcal{W}}\right)$. 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; thus I estimate $\delta^{b'}\beta = \delta^{MAX}\beta + z^f\gamma$ flexibly. The first term $\delta^{MAX}\beta$ 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.[30] The vector z^f includes indicators for whether the firm is public, received multiple loans in the pre-crisis period, and is in the

[30] For instance, Boualam (2015) emphasizes the search frictions inherent to credit reallocation.

manufacturing sector, as well as an intercept.

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

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

This is the model equivalent of the reduced-form correlation described in Section 2.3. The information gap $\mathcal{W}$ as well as γ is estimated via non-linear least squares regression, i.e.

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

The estimated information gap between lenders is 15.13%; detailed estimation results are presented in Table 3. 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 variance of the unobservable ν^f. A moderate magnitude reflects the fact that there is a large amount of information that is unobservable to the econometrician but is known to all lenders, independent of the information gap. This results 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 loans 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) or 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 character-

Parameters	Interpretation	Estimated value	90% confidence interval
$\mathcal{W}$	Information gap	15.13%	[8.31%, 38.57%]
γ	*Shifters of* $\delta^{b'}\beta = \delta^{MAX}\beta + z^f\gamma$		
	Public	0.00	[-0.03, 0.02]
	Multiple pre-crisis loans	-0.02	[-0.04, 0.00]
	Manufacturing	-0.01	[-0.02, 0.02]
	Cross-sectional mean of $\delta^{b'}\beta$	0.31	
	Cross-sectional standard deviation of $\delta^{b'}\beta$	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 3 – Second stage estimation results: main specification

istics. 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 somewhat 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 another consistency check, 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 outside financiers, I find that their information gap is 30% larger relative to public firms. This cross-sectional heterogeneity provides an additional support that the measure $\mathcal{W}$ accurately reflects informational frictions.

As a last validation of the empirical strategy, I reestimate the model after deliberately including fewer controls 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 a third, from 15.13% to 13.52%, as can be seen in Table 13 in the Appendix. 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 *underestimates* the information gap. Finally, Section A.3 in the Appendix redefines how firms are classified as borrowing from a new lender, based on how many informed lenders are in the firm's new crisis syndicate. These results have implications for how easy it is for lenders to share information within a syndicate.

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 4 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:

$$\mathbb{P}_{\mathcal{W}=0}(f \text{ borrows from a new lender}) = \mathbb{P}(\nu_1^f \geq \bar{\nu}(\delta^{b'}, x^f) | \nu_1^f \leq \bar{\nu}(\delta^b, x^f))$$

where the informed lender decision rule $\bar{\nu}$ is estimated in the first stage. For ease of exposition, I measure the extensive margin response of lending by defining the lending rate. The lending rate is computed as $2\times$ share of firms with a loan in 2004–2008 that received a new loan in 2008–2010. The factor of two ensures that a lending rate of 1 implies a stable lending at the extensive margin.

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 point. 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 of loans not made after the crisis because of the information gap. For comparison, Table 4 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-offf yields aggregate effects of \$19 and \$10 billion respectively, while using ABX loading implies a smaller effect.

	Crisis Period Outcome		
		Increase in lending ($bn)	
	Lending rate	using median crisis loan size	using 25th percentile
Data	0.65	-	-
Countefactuals			
(no information gap)			
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]
Other specifications			
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× share of firms with a loan in 2004–2008 that received a new loan in 2008–2010. In the main model, the crisis exposure of a firm's pre-crisis average of the relative fall in lending between 2004–2008 and 2008–2010 of 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 loans 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 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 4 – Aggregate effects of information gap

	Main model	Naive model
Information gap	15.13%	56.65%
Counterfactuals		
Lending rate	0.68	0.74
Increase in lending ($bn)	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 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 5 – Estimates from naive model ignoring the bias introduced by common information ν_1

The bias due to information ν_1^f common to all lenders but unobservable to the econometrician leads to bias when estimating the information gap is the key reason behind using the identification strategy introduced in this paper. To make this point clear, I estimate a naive model that ignores this common information. As 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,

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

where ν^* is the uninformed lender decision rule.

Table 5 shows that the naive model dramatically overestimates the information gap and its effects: both $\mathcal{W}$ and the counterfactual increase in 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 during the Crisis

How important is the information gap relative to other forces? 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 idiosyncratic bank 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 level regression:

$$P(f \text{ borrows during crisis}) = \underbrace{\gamma * \delta^b}_{\text{Previous lender's shock}} + \text{Firm controls} + \epsilon$$

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 previous lender's shock. 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:

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

where $\hat{P}(f$ borrows during crisis) is 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 6 displays the results from this counterfactual exercise, while Table 14 in the Appendix 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 $34 billion more loans being made during 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 implemented *targeted* interventions aimed at providing public support

Crisis period 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× the share of firms with a loan in 2004–2008 that received a new loan in 2008–2010. 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 6 – The aggregate effects of imperfect credit reallocation

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.[31]

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:

$$P(\text{borrow}) = \gamma * \text{Previous lender's shock} + \text{Firm controls} + \epsilon$$

Figure 8 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 crisis exposure of the worst lenders. 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.

[31] These interventions also often have multiple objective, such as preventing bank runs or domino effects.

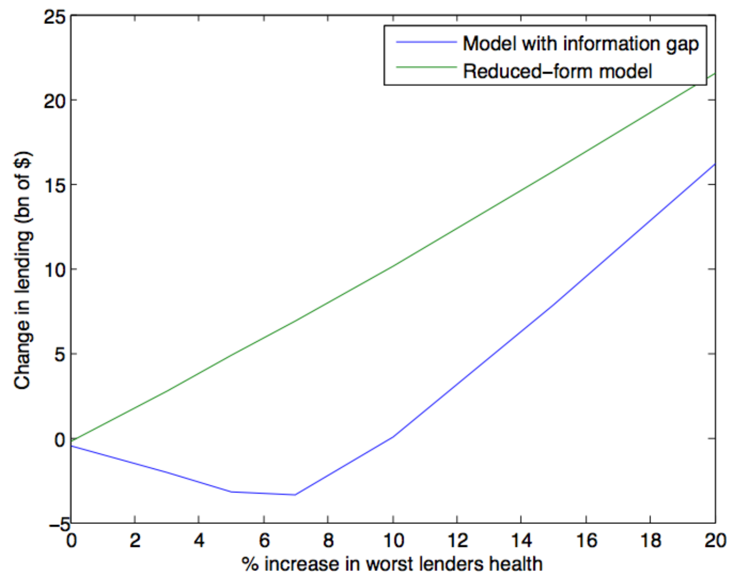
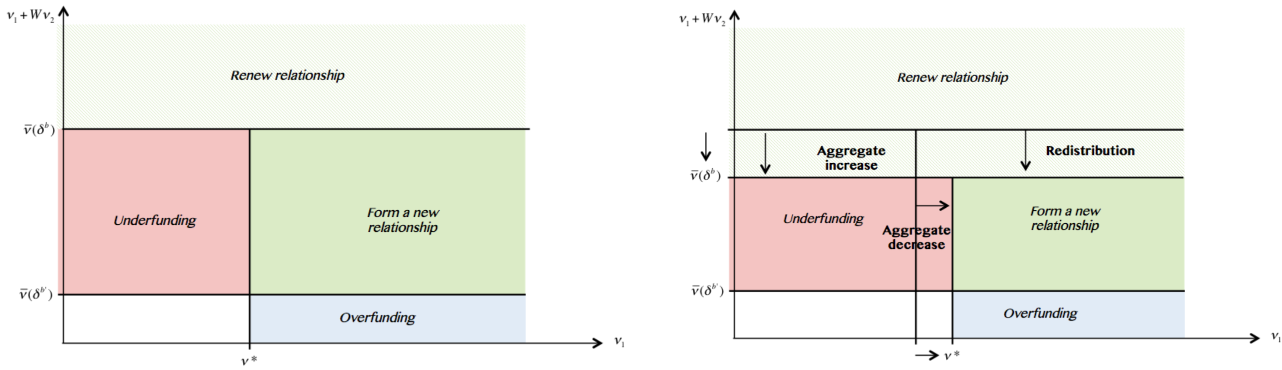


Figure 8 – Unintended consequence of targeted interventions

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 new lenders' inference. There is therefore a second, negative effect on credit reallocation. In fact, Figure 8 shows that for interventions that are not forceful enough, the second effect can dominate. This logic is related to the models of Uhligh (2010) or Malherbe (2014) who study adverse selection in very different settings.

Figure 9 summarizes the economic forces at play. Consider what happens to borrowers with 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 a stricter lending rule ($\nu^* > \bar{\nu}(\delta^{b'})$) and there is therefore an underfunding region.

The right panel of Figure 9 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



(a) Before intervention (b) After intervention

Figure 9 – Impact of targeted intervention: aggregate effect vs. redistribution

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

These results open the following broad question: Could policies aimed at fostering credit reallocation replace some of the interventions supporting the weakest banks? To show how the model estimates can be used to discuss other policy options, I conduct a last counterfactual exercise.

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 approached by a firm in the second stage.[33] Formally, the subsidy is equivalent to reducing the crisis exposure of the new lender proportionally: $\delta^{b' \text{ SUBSIDY}} = \delta^{b'}(1 - s)$.

Figure 10 in the Appendix illustrates the effects of such a policy on aggregate lending. As opposed to interventions targeting the weakest lenders, this type of intervention unambiguously increases 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

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

[33] The 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.

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 represent 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; I leave this question for future research.

7 Conclusion

This paper introduces a novel empirical approach for studying the role of an informational friction limiting the reallocation of credit after a shock to banks. Lenders have private information about their borrowers and this information gap makes switching lenders difficult. At the same time, there is common information that all lenders can observe that the econometrician cannot. 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.

The main contribution of this paper is to address this empirical challenge by estimating a discrete-choice model of relationships with three explicit layers of information. I show how to use bank shocks to identify this private information separately from information common to all lenders. Furthermore, the model estimates can also be used for quantification: beyond documenting its existence, how much does the friction matter? There are many settings in which economists have a reasonable idea of which frictions are at play, but have very little sense of which is the most relevant empirically.

To demonstrate the idea behind the empirical strategy, I apply this approach to the U.S. corporate loan market during the recent financial crisis. I find that the information gap imposed a significant cost on firms looking for new relationships: I estimate that $14 billion more worth of loans would have been made in the counterfactual in which the information gap is zero.

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 fall 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 broker-dealer networks, employment relationships, relationships with a firm's large customers or suppliers, or with professionals such as lawyers or accountants.

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A Appendix

A.1 Additional Tables

	Pre-crisis (Jan 04-Sept 08)		Post-crisis (0ct 08-Dec 10)		
	Mean	Std. Dev.	Mean	Std. Dev.	% change in mean
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 crisis loan is the first new loan received in the 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 7 – Change in loan terms after the crisis

	Outcome: Firm borrows from a new lender, conditional on not borrowing from its pre-crisis lender			
	OLS			IV
	(1)	(2)	(3)	(4)
Pre-crisis lender exposure	0.52	0.62	0.69**	3.26**
	(0.47)	(0.41)	(0.35)	(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 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 inference hypothesis: reduced-form regressions

	Dependent variable:		
	(1) Log post-crisis loan size	(2) Post-crisis loan spread	(3) Post-crisis loan collateralized
New lender dummy	-0.26***	23.7*	0.03
	(0.06)	(13.95)	(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 regressions. $^{*}p < 0.10;^{**} p < 0.05;^{***} p < 0.01$. *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 crisis period. A borrower is classified as borrowing from its pre-crisis lender if at least one lead lender of its 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 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 given by new lenders: OLS regressions

	Outcome: % change in loan size after the crisis	
	(1) FE	(2) OLS
Pre-crisis lender's exposure	-2.28***	-2.35***
	(0.12)	(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 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 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 regressions. 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%
Shifters of $\delta^{b'}\beta = \delta^{MAX}\beta + z^f\gamma$				
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
Mean of $z^f\gamma$	0.31	0.31	0.23	0.19
Standard deviation of $z^f\gamma$	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 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 %
Shifters of $\delta^{b'}\beta = \delta^{MIN} + z^f\gamma$			
Public	0.00	0.00	0.09
Multiple pre-crisis loans	-0.02	0.02	-0.03
Manufacturing	-0.01	0.00	-0.02
Mean of $z^f\gamma$	0.31	0.33	0.67
Standard deviation of $z^f\gamma$	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. A borrower is classified as renewing its relationship if at least one lead lender of its 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 13 – Second stage estimates: alternative specifications

	Outcome: Borrow from any lender		
Pre-crisis lender's exposure	-3.08***	-2.49***	-1.90***
	(1.13)	(0.87)	(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 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× 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 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

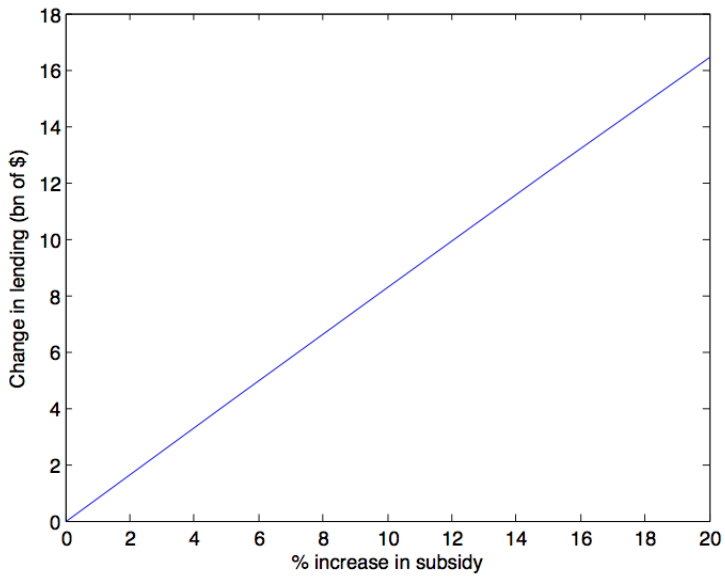

Figure 10 – Unintended consequence of targeted interventions

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(\frac{\bar{\nu}-\nu_1}{\mathcal{W}})}{F_2(\frac{\bar{\nu}-\nu_1}{\mathcal{W}})} \right) \frac{dF_2(\nu_2)}{F_2(\frac{\bar{\nu}-\nu_1}{\mathcal{W}})} \\
&\quad - s(\bar{\nu}, \mu_0, x, r') \frac{f_2(\frac{\bar{\nu}-\nu_1}{\mathcal{W}})}{F_2(\frac{\bar{\nu}-\nu_1}{\mathcal{W}})} \\
&= \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(\frac{\bar{\nu}-\nu_1}{\mathcal{W}})} \\
&\quad + \frac{f_2(\frac{\bar{\nu}-\nu_1}{\mathcal{W}})}{F_2(\frac{\bar{\nu}-\nu_1}{\mathcal{W}})} \int_{\nu_2 \leq \frac{\bar{\nu}-\nu_1}{\mathcal{W}}} \left(s(\nu_1 + \mathcal{W}\nu_2, \mu_0, x, r') - s(\bar{\nu}, \mu_0, x, r') \right) \frac{dF_2(\nu_2)}{F_2(\frac{\bar{\nu}-\nu_1}{\mathcal{W}})} \\
&\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(\frac{\bar{\nu}-\nu_1}{\mathcal{W}})} \\
&\quad + \frac{f_2(\frac{\bar{\nu}-\nu_1}{\mathcal{W}})}{F_2(\frac{\bar{\nu}-\nu_1}{\mathcal{W}})} \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(\nu_1 + \mathcal{W}\nu_2 - \bar{\nu} \right) \frac{dF_2(\nu_2)}{F_2(\frac{\bar{\nu}-\nu_1}{\mathcal{W}})} \\
&= \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(\frac{\bar{\nu}-\nu_1}{\mathcal{W}})}{F_2(\frac{\bar{\nu}-\nu_1}{\mathcal{W}})} (\nu_1 + \mathcal{W}\nu_2 - \bar{\nu}) \right) \frac{dF_2(\nu_2)}{F_2(\frac{\bar{\nu}-\nu_1}{\mathcal{W}})} \\
&> \int_{\nu_2 \leq \frac{\bar{\nu}-\nu_1}{\mathcal{W}}} k \left(1 + \frac{f_2(\frac{\bar{\nu}-\nu_1}{\mathcal{W}})}{F_2(\frac{\bar{\nu}-\nu_1}{\mathcal{W}})} (\nu_1 + \mathcal{W}\nu_2 - \bar{\nu}) \right) \frac{dF_2(\nu_2)}{F_2(\frac{\bar{\nu}-\nu_1}{\mathcal{W}})} \\
&> 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).

Lemma 2: 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 $\bar{\nu}(\mu_0, x^f, \delta^{b'})$.

Proof : 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:

$$\begin{aligned}
s(\nu_{FI}, \mu_0, x, r') &= 0 && (11) \\
&= \int_{\nu_2 \leq \frac{\bar{\nu}-\nu_1}{\mathcal{W}}} s(\nu^* + \mathcal{W}\nu_2, \mu_0, x, r') \frac{dF_2(\nu_2)}{F_2(\frac{\bar{\nu}-\nu_1}{\mathcal{W}})} && (12) \\
&\leq s(\nu^* + \mathcal{W} \int_{\nu_2 \leq \frac{\bar{\nu}-\nu_1}{\mathcal{W}}} \nu_2 \frac{dF_2(\nu_2)}{F_2(\frac{\bar{\nu}-\nu_1}{\mathcal{W}})}, \mu_0, x, r') && (13) \\
&< s(\nu^*, \mu_0, x, r') && (14)
\end{aligned}$$

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

A.3 Information Sharing across Lenders

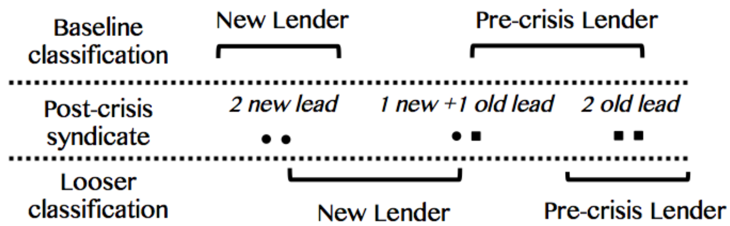

Figure 11 – Test for information sharing within lending syndicate

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 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. This 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.