Adverse Selection and Intermediation Chains *

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We propose a parsimonious model of over-the-counter trading with asymmetric information to explain the existence of intermediation chains that stand between buyers and sellers of assets. Trading an asset through multiple intermediaries can preserve the efficiency of trade by reallocating an information asymmetry over many sequential transactions. An intermediation chain that involves heterogeneously informed agents helps to ensure that the adverse selection problems counterparties face in each transaction are small enough to allow for socially efficient trading strategies by all parties involved. Our model makes novel predictions about network formation and rent extraction when adverse selection problems impede the efficiency of trade.

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JEL Codes: G20, D82, D85

1 Introduction

Transactions in decentralized markets often feature the successive participation of several intermediaries. For example, Viswanathan and Wang (2004, p.2) note that in foreign exchange markets "much of the inter-dealer trading via direct negotiation is sequential (an outside customer trades with dealer 1 who trades with dealer 2 who trades with dealer 3 and so on) and involves very quick interactions".[1] Adrian and Shin (2010, p.604) argue that, more broadly, the whole U.S. financial system has shifted in recent decades from its traditional, centralized model of financial intermediation to a more complex, market-based model characterized by "the long chain of financial intermediaries involved in channeling funds" (see also Kroszner and Melick 2009, Cetorelli, Mandel, and Mollineaux 2012, Pozsar et al. 2013, for similar characterizations).

In this paper, we propose a parsimonious model that rationalizes the existence of intermediation chains. We show that chains of heterogeneously informed agents can fulfill an important economic role in intermediating trade by reallocating information asymmetries over multiple sequential transactions. Our model considers two asymmetrically informed agents who wish to trade an asset over the counter (OTC) in order to realize exogenous gains to trade (for example, for liquidity reasons). One agent is assumed to be an expert who is well informed about the value of the asset, whereas the other agent is uninformed. A standard result in models like ours is that trade breaks down between agents when the potential gains to trade are small relative to the degree of information asymmetry about the asset's value. In that case, we show that involving heterogeneously informed agents — whose information quality ranks between that of the ultimate buyer and that of the seller — to intermediate trade can improve trade efficiency. In contrast to other intermediation theories in which one intermediary suffices to eliminate inefficient behavior, our simple mechanism can explain why trading often goes through chains of intermediaries rather than through simpler trading networks centered around one dominant broker. We show that trade efficiency can be improved by reallocating the adverse selection problem over a large number of sequential transactions as long as the difference in information quality is small between the two counterparties involved in each transaction.

The original adverse selection problem between a buyer and a seller is reallocated in a non-linear

[1] We will refer, later in the introduction, to other papers that document the existence of intermediation chains in various markets.

fashion when several heterogeneously informed intermediaries are involved. Each pair of sequential traders bargains based on conditional distributions for the value of the asset that are different than the distribution that characterizes the original information asymmetry without intermediaries. It is then crucial to have intermediaries located within the trading network such that each trader's information set is similar, although not identical, to that of nearby traders (i.e., his counterparties). For large adverse selection problems a high number of intermediaries is therefore needed to sufficiently reduce the information asymmetry that each agent faces when it is his turn to trade the asset. Greater information asymmetries require longer intermediation chains and, overall, more trading across agents, which contrasts with the conventional wisdom that asymmetric information should be associated with low trading volume (as was the case in the seminal model of Akerlof 1970).

However, each trader involved in such a network needs to be privately incentivized to sustain trade and preserve the surplus. The conditional distributions for the value of the asset that each heterogeneously informed trader and his counterparty face determine their incentives to trade efficiently. Our model thus speaks to how trading networks impact the ability of all involved parties to extract rents and their willingness to sustain socially efficient trade in equilibrium. In some cases, the intermediaries extract more rents through informed trading than the additional surplus they create by increasing liquidity. In those cases, intermediaries are willing to compensate other traders to secure a place in the socially optimal trading network. We characterize order-flow agreements that guarantee that every agent involved benefits from the implementation of a socially efficient network. These agreements, which allow to implement intermediated trade in equilibrium, are consistent with the practice by financial intermediaries of offering cash payments, or subsidized services, to traders in exchange for their order flow.[2] The socially beneficial role that order-flow agreements can play in our model challenges recent proposals by regulatory agency and stock exchange officials to ban related practices.[3]

Intermediation has been known to facilitate trade, either by minimizing transaction costs

[2]See, e.g., Blume (1993), Chordia and Subrahmanyam (1995), Reuter (2006), and Nimalendran, Ritter, and Zhang (2007) for empirical evidence.

[3]See, for example, the comments made by Jeffrey Sprecher, CEO of IntercontinentalExchange (which owns the New York Stock Exchange), reported in "ICE CEO Sprecher wants regulators to look at 'maker-taker' trading" by Christine Stebbins on Reuters.com (January 26, 2014), the document titled "Guidance on the practice of 'Payment for Order Flow' " prepared by the Financial Services Authority (May 2012), and the comments made by Harvey Pitt, former Securities and Exchange Commission Chairman, reported in "Options Payment for Order Flow Ripped" by Isabelle Clary in Securities Technology Monitor (May 3, 2004).

(Townsend 1978), by concentrating monitoring incentives (Diamond 1984), or by alleviating search frictions (Rubinstein and Wolinsky 1987, Yavaş 1994, Duffie, Gârleanu, and Pedersen 2005, Neklyudov 2013). Our paper, however, specifically speaks to how intermediaries may solve asymmetric information problems. We already know from Myerson and Satterthwaite (1983) that an uninformed third party who subsidizes transactions can help to eliminate these problems in bilateral trade. Trade efficiency can also be improved by the involvement of fully informed middlemen who care about their reputation (Biglaiser 1993) or who worry that informed buyers could force them to hold on to low-quality goods (Li 1998). Contrary to these models, our model considers the possibility that an intermediary's information set differs from that of the agents initially involved in a transaction. In fact, in our static model without subsidies, warranties, or reputational concerns the involvement of an intermediary who is either fully informed or totally uninformed does not improve trade efficiency. Thus, the insight that moderately informed intermediaries can reduce trade inefficiencies simply by layering an information asymmetry over many sequential transactions fundamentally differentiates our paper from these earlier papers.

Rationalizing intermediation chains, which are observed in many financial markets, also distinguishes our paper from many market microstructure models with heterogeneously informed traders but where trading among intermediaries plays no role. Examples of those models include Kyle (1985) and Glosten and Milgrom (1985), where competitive market makers learn from order flow data and intermediate trade between liquidity traders and informed traders, and Jovanovic and Menkveld (2012), where high frequency traders learn quickly about the arrival of news and intermediate trade between early traders who post a limit order and late traders who react to the limit order using information that became available since its posting. The optimal involvement of multiple intermediaries also distinguishes our paper from Babus (2012) who endogenizes OTC trading networks when agents meet sporadically and have incomplete information about other traders' past behaviors. In equilibrium, a central intermediary becomes involved in all trades and heavily penalizes anyone defaulting on prior obligations.[4]

On the other hand, Gofman (2011) allows for non-informational bargaining frictions in an OTC network and shows that socially optimal trading outcomes are easier to achieve if the network is

[4]See also Farboodi (2014) who shows that a centralized trading network is socially optimal when banks must establish credit relationships prior to learning about the allocation of investment projects in the economy.

sufficiently dense (although the relationship is not necessarily monotonic). In our model, a trading network needs to be sparse enough to sustain efficient trade; otherwise, uninformed traders might be tempted to contact socially inefficient counterparties, in an attempt to reduce the number of strategic, informed intermediaries trying to extract surplus away from them. (We analyze the role that order-flow agreements can play in alleviating this problem.) Our paper also relates to Malamud and Rostek (2013) who study the concurrent existence of multiple exchanges in decentralized markets. Creating a new private exchange may improve the liquidity in incumbent exchanges by reducing the price impact that strategic traders impart when simultaneously trading the same asset at different prices on multiple exchanges. This particular mechanism plays no role in our model as trading is bilateral, occurs sequentially among intermediaries, and entails a fixed transaction size.

Although our framework could be used to shed light on the existence of intermediation chains in many contexts, we rely on the empirical literature on financial markets to contextualize our theory. In addition to the discussions in Viswanathan and Wang (2004) and Adrian and Shin (2010) mentioned earlier, many papers document the importance of transactions among intermediaries, a key prediction of our model, in centralized and decentralized financial markets.[5] For example, in foreign exchange markets inter-dealer transaction volume averages $2.1 trillion per day, according to a 2013 report by the Bank of International Settlements. For metals futures contracts, Weller (2013) shows that a median number of 2 intermediaries are involved in round-trip transactions and up to 10% of transactions involve 5 or more intermediaries. In municipal bond markets, Li and Schürhoff (2014) show that 13% of intermediated trades involve a chain of 2 intermediaries and an additional 10% involve 3 or more intermediaries. Hollifield, Neklyudov, and Spatt (2014) also find evidence of intermediation chains for many securitized products: for example, intermediated trades of non-agency collateralized mortgage obligations involve 1.76 dealers on average and in some instances the chain includes up to 10 dealers.

Viswanathan and Wang (2004) show that the issuer of a security may prefer to have a set of dealers, heterogeneous only in their inventory levels, sequentially trading the security over having those same dealers participating in a centralized auction where the supply of the security is split

[5]See, e.g., Gould and Kleidon (1994) for Nasdaq stocks, Reiss and Werner (1998) and Hansch, Naik, and Viswanathan (1998) for London Stock Exchange stocks, Lyons (1996) for foreign exchange instruments, Weller (2013) for metals futures, Hollifield, Neklyudov, and Spatt (2014) for securitized products, and Li and Schürhoff (2014) for municipal bonds.

among them. The arguments highlighted in their model are based on differences in how strategic dealers can behave when trading bilaterally versus participating in a centralized auction — sequential bilateral trading allows a dealer who just bought a security to act as a monopolist and control the price and inventory levels in later periods. A few empirical papers such as Hansch, Naik, and Viswanathan (1998) document that inventory management motives explain part of the trading among intermediaries in financial markets, but key features of inter-dealer trading still remain unexplained. For example, Manaster and Mann (1996) show that the positive relationship between trader inventories and transaction prices in futures trading data violates the predictions of inventory control models such as Ho and Stoll (1983). Manaster and Mann (1996, p.973) conclude that the intermediaries they study are "active profit-seeking individuals with heterogeneous levels of information and/or trading skill", elements that are usually absent from inventory control theories.[6] Our model proposes an information-based explanation for intermediation chains, by combining asymmetric information with inventory management motives.[7] The intermediaries in our model are effectively averse to holding inventories (i.e., non-zero positions) since they are not the efficient holders of the asset, that is, those who realize the gains to trade. Yet, information asymmetries may prevent them from offloading the asset to potential buyers and creating a surplus.

Recent empirical evidence appears to lend support to the main predictions from our model. In particular, Li and Schürhoff (2014) show that municipal bonds without a credit rating are more likely to be traded through long intermediation chains than municipal bonds with a credit rating (which arguably are less likely to be associated with large adverse selection problems). They also show that the average round-trip spread paid to dealers increases with the length of the chain. Hollifield, Neklyudov, and Spatt (2014) also show that securitized products such as non-agency collaterized mortgage obligations that can be traded by unsophisticated and sophisticated investors (i.e., "registered" instruments) are usually associated with longer chains of transactions and higher spreads paid to dealers (often viewed as a measure of adverse selection) than comparable instruments that can only be traded by sophisticated investors (i.e., "rule 144a" instruments). These

[6]See also Glosten and Harris (1988), Stoll (1989), Foster and Viswanathan (1993), Hasbrouck and Sofianos (1993), Madhavan and Smidt (1993), and Keim and Madhavan (1996) for early evidence that information asymmetries affect intermediated transactions in financial markets.

[7]Madhavan and Smidt (1993) also combine asymmetric information and inventory management motives, but their model remains silent about the empirical phenomenon of intermediation chains; their model features centralized trading, rather than OTC trading, and does not allow for multiple intermediaries.

findings are all consistent with our model's predictions that larger information asymmetries require longer intermediation chains, more inter-dealer trade, and are associated with larger rents being captured by intermediaries.

In the next section, we model a simple, and fairly standard, adverse selection problem between two asymmetrically informed traders. We show in Section 3 how adding moderately informed intermediaries can alleviate this adverse selection problem. We study in Section 4 how order-flow agreements can be used to ensure that a socially optimal intermediation chain becomes privately optimal to implement for all traders involved. In Section 5, we show how our results can be extended to various information structures, and the last section concludes.

2 The Adverse Selection Problem

We start by assuming two risk-neutral agents who consider trading one unit of an asset over the counter: the current owner who values the asset at v and a potential buyer who values it at $v + \Delta$. A potential interpretation for this interaction is that of a firm that wishes to offload a risk exposure (e.g., to interest rates, foreign exchange rates, or commodity prices) and meets an expert able to hold the risk exposure more efficiently (e.g., by means of pooling or diversification). The firm, also referred to as the seller, is thus trying to sell a risky asset to the expert, also referred to as the buyer, because the expert values the asset more than the firm does. Trade is then labeled as efficient only if the asset ends up in the hands of the expert with probability 1 and the gains to trade Δ are always realized.

We assume the gains to trade Δ are constant and known to all agents, but the common value v is uncertain and takes the form:

$$v = \sum_{n=1}^{N} \phi_n \sigma,$$

where the N factors $\phi_n \in \{0, 1\}$ are drawn independently from a Bernoulli distribution with $\Pr[\phi_n = 1] = 1/2$. The common value is thus binomial distributed with $v \sim B\left(N, \frac{1}{2}\right)$. We denote by Φ the full set of factor realizations $\{\phi_1, \phi_2, ..., \phi_N\}$.[8]

Although the role that intermediation will play in our model is relatively simple, multi-layered

[8]Shin (2003) also assumes a Binomial distribution, albeit a multiplicative one, to model uncertain asset values. His paper's focus, however, differs from ours and pertains to the optimal disclosure of information by a manager and its effects on asset prices.

bargaining problems with asymmetric information are usually complex to analyze given the potential for multiple equilibria arising from the various types of off-equilibrium beliefs. We therefore make a few stylized assumptions that will allow us to keep the model sufficiently tractable, even when we consider in Section 3 multiple sequential transactions occurring among a large number of heterogeneously informed traders.

First, we assume that, in any transaction, the current holder of the asset makes an ultimatum offer (i.e., quotes an asking price) to his counterparty. Focusing on ultimatum offers simplifies the analysis of equilibrium bidding strategies and is consistent with the characterization of sequential inter-dealer trading by Viswanathan and Wang (2004, p.3) as "very quick interactions". Ultimatum offers are also consistent with how Duffie (2012, p.2) describes the typical negotiation process in OTC markets and the notion that each OTC dealer tries to maintain "a reputation for standing firm on its original quotes." Here, it is the seller who quotes a price rather than the buyer who makes an offer, but we show later how our results also apply to alternative settings, including one in which the buyer makes the ultimatum offer (see Subsection 5.3).

Second, we assume that prior to trading the seller is uninformed about the realizations of ϕ_n that determine the common value v, whereas the expert observes the full set Φ of factor realizations. Note that for many financial products endowing a "buyer" with the informational advantage rather than the "seller" is an unrestrictive assumption; for example, a firm could be viewed as the buyer of an insurance policy, or, alternatively, as the seller of a risk exposure. In Section 5, we consider alternative information structures, including a case with an expert seller and a case with two-sided asymmetric information.

Third, agents know how well informed their counterparties are, that is, the set of factors that each agent observes is common knowledge.[9] Although traders in our setting are asymmetrically informed about the common value component v, all traders know the quality of the information available to their counterparties. Seppi (1990) lends support to this assumption arguing that agents knowing the identity of their trading counterparties is an important distinction between OTC trading and centralized/exchange trading.

Together, these three assumptions eliminate signaling concerns from our model and guarantee

[9] Morris and Shin (2012) relax the common-knowledge assumption in a bilateral trading setup similar to the one in this section and show how the resulting coordination problems can magnify the effect of adverse selection on trade efficiency.

the uniqueness of our equilibrium without the need for equilibrium refinements. We are, thus, able to derive closed-form solutions for many objects of interest that would otherwise be hard to uniquely pin down. For example, the following lemma characterizes a limited set of price quotes the seller chooses from when trading directly with the expert buyer.

Lemma 1 (Price candidates under direct trade) *If the seller and the expert buyer trade directly, the seller optimally chooses to quote one of $(N+1)$ price candidates p_i, where p_i is defined as:*

$$p_i = i\sigma + \Delta, \quad i \in \{0, ..., N\}.$$

The unconditional probability with which the expert buyer accepts a price quote p_i is given by:

$$\pi_i = \sum_{k=0}^{N-i} \binom{N}{k} \left(\frac{1}{2}\right)^N.$$

Proof. The expert buyer optimally accepts to pay a given price $\tilde{p}$ if and only if $\tilde{p} \leq v + \Delta$. Given the Binomial distribution for v, the price candidates $p_i = i\sigma + \Delta$ for $i \in \{0, ..., N\}$ represent the maximum prices the seller can charge conditional on ensuring any given feasible acceptance probability. Further, the seller strictly prefers the price quote p_N to non-participation, since quoting p_N increases his average payoff by $\frac{1}{2^N}\Delta$. ■

For trade to be efficient and occur with probability one, the seller must find it optimal to quote p_0 in equilibrium rather than any other price candidate p_i for which $i \in \{1, ..., N\}$. The following proposition provides a necessary and sufficient condition on the fundamentals of the asset (σ, Δ, N) to ensure efficient trade when the seller and the buyer trade directly with each other.

Proposition 1 (Efficient direct trade) *Direct trade between the seller and the expert buyer is efficient if and only if:*

$$\frac{\sigma}{\Delta} \leq \frac{1}{2^N - 1}. \tag{1}$$

Under efficient trade, the expected surplus from trade is split between the seller who obtains $\Delta - \frac{N}{2}\sigma$ and the buyer who obtains $\frac{N}{2}\sigma$.

Proof. Lemma 3, which is provided in Appendix A, shows that the incentive to increase the price quote from p_i to p_{i+1} is strongest at $i = 0$ and the condition for the seller to prefer a price quote p_0 over p_1 also implies that he prefers quoting p_0 over any p_i for which $i \in \{1, ..., N\}$. A seller who decides to quote p_1 rather than p_0 receives a higher price ($p_1 - p_0 = \sigma$) with probability $1 - \left(\frac{1}{2}\right)^N$, but forgoes extracting the gains to trade Δ with probability $\left(\frac{1}{2}\right)^N$. The seller thus chooses to quote p_0 among all prices if and only if doing so generates a weakly higher expected payoff than quoting p_1:

$$\begin{aligned} \pi_0 p_0 &\geq \pi_1 p_1 + (1 - \pi_1) \cdot 0 \\ \Leftrightarrow \Delta &\geq \left(1 - \left(\frac{1}{2}\right)^N\right)(\sigma + \Delta) . \end{aligned}$$

Eqn. (1) follows directly from the last inequality. Under efficient trade, the seller collects a surplus of:

$$p_0 - E[v] = \Delta - \frac{N}{2}\sigma$$

and the buyer collects an expected surplus of:

$$E[v] + \Delta - p_0 = \frac{N}{2}\sigma.$$

■

Efficient trade is thus only possible for small enough values of $\frac{\sigma}{\Delta}$, which quantifies the price concession made by the seller when quoting the lowest price p_0 relative to the gains to trade he extracts from sustaining trade. When $\frac{\sigma}{\Delta}$ is high and the information asymmetry is large relative to the surplus created by trade, trade breaks down with probability $\left(\frac{1}{2}\right)^N$ or greater and at least $\frac{\Delta}{2^N}$ in surplus from trade is destroyed.[10]

Next, we will show that a trading network that splits the information asymmetry over a sequence of transactions can induce fully efficient behavior on the part of heterogeneously informed traders. Although other mechanisms have been proposed to solve adverse selection problems (see,

[10] Asymmetric information could also affect the gains to trade Δ rather than only affecting the common value v as is the case in our model. For example, gains to trade could be influenced by private information about a dealer's order flow. We know, however, from Myerson and Satterthwaite (1983) that inefficient trading being a consequence of asymmetric information is a common result in bilateral bargaining, and we simplify the analysis by focusing on only one type of information asymmetry.

for example, the literature on optimal security design which includes: DeMarzo 2005, Chakraborty and Yilmaz 2011, Yang 2013), the idea that intermediation chains can by themselves fully alleviate these problems is novel and may shed light on the fact that chains are frequently observed in decentralized markets.

3 Intermediation Chains

In this section, we consider the involvement of M intermediaries who observe different *subsets* of Φ, the full set of factor realizations ϕ_n. Like the seller, these intermediaries privately value the asset at v and thus cannot help realize gains to trade unless they resell the asset and thereby facilitate a more efficient allocation. Moreover, these intermediaries do not bring new information to the table, as their information sets are nested by that of the expert buyer. However, as we show below, an intermediation chain that involves heterogeneously informed traders can improve the efficiency of trade by reallocating an information asymmetry over several sequential transactions.

Consider a simple trading network in which the uninformed firm offers to sell the asset to intermediary 1. If trade occurs, intermediary 1 offers to sell the asset to the next trader in the network, intermediary 2. Conditional on trade occurring, these bilateral interactions are repeated up until we reach the end of the chain, where intermediary M offers to sell the asset to the expert buyer. (To simplify the notation, we label the firm/seller as trader 0 and the expert buyer as trader $M + 1$.) Traders are not allowed to deviate from the trading network by bypassing the trader who is next in line in the intermediation chain (we further discuss this assumption and its link to order-flow agreements in Section 4). Further, consistent with how we modeled trading without intermediaries, we assume that whoever owns the asset and tries to sell it quotes an ultimatum price to his counterparty.

The M intermediaries are assumed to be heterogeneously informed, as it is often the case in OTC markets. In fact, the main mechanism that makes intermediation valuable in our model can be highlighted best by assuming that the subset of factor realizations that intermediary m observes before trading is nested by the subset of factor realizations that intermediary $m+1$ observes before trading: $\Phi_m \subseteq \Phi_{m+1} \subseteq \Phi$, for $m \in \{0, 1, ..., M\}$. Trader 1 is thus assumed to be the intermediary with the least expertise, as he only observes realizations from N_1 factors, say $\{\phi_1, \phi_2, ..., \phi_{N_1}\}$, which can be interpreted as information that is relatively cheap to acquire and easy to interpret. Trader 2 observes the same N_1 factors $\{\phi_1, \phi_2, ..., \phi_{N_1}\}$ as well as $(N_2 - N_1)$ extra factors that are a little bit harder or more expensive to gather. The same logic applies for the remaining traders in the chain up until the expert (i.e., trader $M + 1$) is reached who observes all factors in the set Φ. This simple network with increasingly informed traders implies that the information set of the proposer of a price quote is always weakly dominated by the responder's information set. Figure 1 shows an example of information sets in a trading network with two intermediaries.

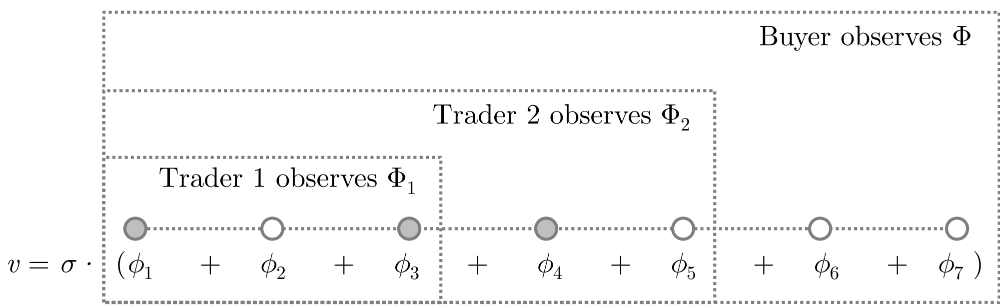

Figure 1: **Example of information sets in trading network.** The figure illustrates our informational structure when two intermediaries are involved ($M = 2$) in trading an asset whose common value v depends on seven factors ϕ_i ($N = 7$). The dotted rectangles indicate the set of factor realizations that are observable to the two intermediaries and to the expert buyer (remember: the firm/seller observes none of these factors). Factor realizations $\phi_i \in \{0, 1\}$ are indicated by the circles that are either unfilled (for $\phi_i = 0$) or filled (for $\phi_i = 1$). The seller is uninformed and thus does not observe any of the factor realizations.

Nesting traders' information sets eliminates signaling concerns and ensures a unique equilibrium despite the fact that we consider $(M + 1)$ bargaining problems among $(M + 2)$ heterogeneously informed agents. Moreover, the recursive nature of our model yields a clean and transparent analytical proof of our main result: an intermediation chain can preserve the efficiency of trade in situations in which surplus would be destroyed if trade were to occur through fewer intermediaries. As will become clear soon, what ultimately contributes to sustaining efficient trade is that the chain reduces the distance in counterparties' information sets, although information sets do not necessarily have to be nested for our mechanism to work. In Section 5, we will show that if information sets are non-nested initially but information percolates through trade as in Duffie, Malamud, and Manso (2009, 2013), a similar mechanism arises, as the asset is held by increasingly better informed agents through the chain. In addition, we will relax the assumption of one-sided asymmetric information and show how the proposed mechanism survives if both the buyer and the seller have private information about the value of the asset.

The proposition below formalizes our main result and is followed by the analysis of two special cases that help to illustrate the intuition behind our result.

Proposition 2 (Efficient trade in an intermediation chain) *Trade is efficient throughout the trading network if and only if:*

$$\frac{\sigma}{\Delta} \leq \min_{m\in\{0,1,...,M\}} \frac{1}{2^{(N_{m+1}-N_m)} + \frac{N-N_{m+1}}{2} - 1}. \tag{2}$$

Under efficient trade, the expected surplus from trade is split between the original seller who obtains $\Delta - \frac{N}{2}\sigma$ *and each trader* $m \in \{1, ..., M+1\}$ *who obtains* $\left(\frac{N_m - N_{m-1}}{2}\right)\sigma$.

Proof. Consider a situation in which trader m currently holds the asset and tries to sell it to trader $m+1$. Trader m knows that G_m of the N_m factor realizations he observes have a value of 1. Similarly, trader $m+1$ knows that G_{m+1} of the N_{m+1} factor realizations he observes have a value of 1. The condition that information sets satisfy $\Phi_m \subseteq \Phi_{m+1} \subseteq \Phi$ implies that $0 \leq N_m \leq N_{m+1} \leq N$ and $0 \leq G_m \leq G_{m+1} \leq N$. Assume for now that whenever trader $m+1$ acquires the asset, subsequent trading is efficient, which requires that traders $k \in \{m+1, m+2, ..., M\}$ each charge a price:

$$p_0^k = G_k\sigma + \Delta,$$

and maximize subsequent trade probability. Trader m then chooses to quote one of $(N_{m+1}-N_m+1)$ price candidates defined as:

$$p_i^m = (G_m + i)\,\sigma + \Delta, \quad i \in \{0, ..., N_{m+1} - N_m\}.$$

The weakly better informed trader $m+1$ only accepts to pay a price p_i^m if it is weakly lower than the price he plans to quote to trader $m+2$, that is, $p_0^{m+1} = G_{m+1}\sigma + \Delta$. For trade to be efficient between traders m and $m+1$, trader m must find it optimal to quote p_0^m in equilibrium rather than any other price candidate p_i^m. Lemma 3 in Appendix A shows that trader m finds optimal to quote p_0^m rather than any other p_i^m if and only if quoting p_0^m makes him wealthier in expectation than quoting p_1^m:

$$\begin{aligned} G_m\sigma + \Delta &\geq \left(1 - \left(\frac{1}{2}\right)^{(N_{m+1}-N_m)}\right)\left[\left(G_m+1\right)\sigma + \Delta\right] + \left(\frac{1}{2}\right)^{(N_{m+1}-N_m)}\left(G_m + \frac{N-N_{m+1}}{2}\right)\sigma \\ \Leftrightarrow \frac{\sigma}{\Delta} &\leq \frac{1}{2^{(N_{m+1}-N_m)} + \left(\frac{N-N_{m+1}}{2}\right) - 1}. \end{aligned}$$

Recursively applying this condition to each trading stage yields the following condition for efficient trade throughout the trading network:

$$\frac{\sigma}{\Delta} \leq \min_{m\in\{0,1,\ldots,M\}} \frac{1}{2^{(N_{m+1}-N_m)} + \left(\frac{N-N_{m+1}}{2}\right) - 1}.$$

Under efficient trade, each trader $m \in \{1, ..., M\}$ collects an expected surplus of:

$$\begin{aligned} E\left[p_0^m|\Phi_{m-1}\right] - p_0^{m-1} &= G_{m-1}\sigma + \left(\frac{N_m - N_{m-1}}{2}\right)\sigma + \Delta - \left[G_{m-1}\sigma + \Delta\right] \\ &= \left(\frac{N_m - N_{m-1}}{2}\right)\sigma, \end{aligned}$$

the final buyer (trader $M+1$) collects an expected surplus of:

$$\begin{aligned} E\left[v|\Phi_M\right] + \Delta - p_0^M &= G_M\sigma + \left(\frac{N - N_M}{2}\right)\sigma + \Delta - \left[G_M\sigma + \Delta\right] \\ &= \left(\frac{N - N_M}{2}\right)\sigma, \end{aligned}$$

and the initial seller (trader 0) collects an expected surplus of:

$$\Delta - E\left[v\right] = \Delta - \frac{N}{2}\sigma.$$

■

The proposition formalizes the intuition that an asset characterized by (σ, Δ, N) is more likely to be traded efficiently within a network if informational advantages between sequential trading partners $(N_{m+1} - N_m)$ are small. By focusing on traders' behavior along the efficient trading path, we are able to exploit the recursivity of the sequence of transactions and show in a tractable way how intermediation chains can help to solve an adverse selection problem. Formally, the condition in eqn. (2) for efficient trade is weakly less restrictive than the corresponding condition in eqn. (1) for the case without intermediaries. (In fact, due to the recursive nature of our model, eqn. (2) corresponds to eqn. (1) when we set $M = 0$.)

The holder of an asset faces the following trade-off when choosing the price he quotes to his counterparty. If the conditions for efficient trade are satisfied for all subsequent transactions in the chain, the prospective seller recognizes that subsequent trading will preserve the whole gains to trade Δ. Hence, he compares the benefit of extracting the full Δ with the cost of quoting a price that is low enough to be accepted by a counterparty who possesses an informational advantage of $(N_{m+1} - N_m)$ factors. When a trader faces a counterparty who is significantly better informed than him, he might find optimal to quote a high price, in case the informed counterparty receives good signals and accepts to pay the high price. However, this strategy also comes at a cost since the asking price may sometimes exceed the counterparty's valuation of the asset. Although such trading strategies may be privately optimal for less informed traders, they are socially inefficient since the surplus from trade is destroyed with positive probability. Transactions between more homogenously informed agents give asset holders lower incentives to quote inefficiently high prices as marginally better informed counterparties are less likely to accept such high offers. Intermediation chains can thus preserve efficient trade in situations in which trade would otherwise break down with positive probability.

Moreover, as the ratio $\frac{\sigma}{\Delta}$ increases and the adverse selection problem worsens, a higher number of intermediaries M are needed to sufficiently bound the information asymmetries that each trading counterparty faces, consistent for example with Li and Schürhoff (2014) who show that municipal bonds with no credit rating are typically traded through longer intermediation chains than municipal bonds with a credit rating (which arguably are less likely to be associated with large adverse selection problems). Specifically, it is easy to show that adding intermediaries helps to relax the restriction imposed on $\frac{\sigma}{\Delta}$ in Proposition 2. Suppose an intermediary m' is added between traders m and $m + 1$. If the expertise of intermediary m' differs from that of those already involved in the chain, in particular if $N_m < N_{m'} < N_{m+1}$, the terms on the right-hand side of eqn. (2) should weakly increase for all layers of transactions. First, all terms on the right-hand side of (2) that do not involve trader m' remain the same as before. Second, both of the terms that involve trader m' are strictly greater than the old term they replace:

$$\frac{1}{2^{(N_{m+1}-N_{m'})}+\frac{N-N_{m+1}}{2}-1}>\frac{1}{2^{(N_{m+1}-N_{m})}+\frac{N-N_{m+1}}{2}-1},$$

and

$$\frac{1}{2^{(N_{m'}-N_{m})}+\frac{N-N_{m'}}{2}-1}>\frac{1}{2^{(N_{m+1}-N_{m})}+\frac{N-N_{m+1}}{2}-1}.$$

The socially optimal response to greater information asymmetries is thus longer intermediation chains and more trading among all agents involved.

The proposition also shows that, given equal informational distances between bilateral counterparties (i.e., the same $(N_{m+1}-N_m)$ for all m), efficient trade is hardest to sustain at the beginning of the chain where less is known about the overall value of the asset. Early in the chain, the expected value of the asset linked to the factors that are unknown to trading counterparties is greater, which makes the possibility of charging a high price and being stuck with the asset less costly than it is late in the chain.

Conditional on efficient trade throughout the network, each informed trader collects rents that increase with the uncertainty in asset value, σ, as well as with his informational advantage over the trader that sells him the asset, (N_m-N_{m-1}). These rents come from the optimality for trader $m-1$ to charge a low price to trader m in order to ensure his full participation in the trade and preserve the whole gains to trade Δ. Trader m only pays $G_{m-1}\sigma+\Delta$ and expects to collect $G_m\sigma+\Delta$. The intermediary sector as a whole is therefore able to extract rents of $\frac{N_M}{2}\sigma$ in total. Among the networks that sustain efficient trade, networks with fewer, more distanced, intermediaries increase the rents that accrue to the expert as well as the average rent a moderately informed intermediary extracts. Our model thus makes predictions about how surplus from trade should be distributed among heterogeneously informed OTC market participants and contributes to the literature on rent-extraction in finance (Murphy, Shleifer, and Vishny 1991, Philippon 2010, Bolton, Santos, and Scheinkman 2012, Glode, Green, and Lowery 2012, Biais and Landier 2013, Glode and Lowery 2013).

To further illustrate how moderately informed intermediaries can help to solve an adverse selection problem between two asymmetrically informed traders, we now analyze two special cases of our model (with $N = 2$ and $N = 3$, respectively).

Two-Factor Case: Suppose an asset is worth $v = \phi_1\sigma + \phi_2\sigma$ to the seller and $v + \Delta$ to the buyer. Without an intermediary, the seller chooses to quote one of three price candidates: (i) Δ, which is accepted by the buyer with probability 1; (ii) $\sigma + \Delta$, which is accepted with probability 3/4; (iii) $2\sigma + \Delta$, which is accepted with probability 1/4.

The first price candidate Δ splits the surplus from trade such that the seller collects $\Delta - \sigma$ and the buyer collects σ. The second price candidate $\sigma + \Delta$ produces an expected surplus of $\frac{3}{4}\Delta - \frac{1}{4}\sigma$ for the seller and $\frac{1}{4}\sigma$ for the buyer. The third price candidate produces an expected surplus of $\frac{1}{4}\Delta$ for the seller and no surplus for the buyer. Quoting the low price Δ is thus optimal for the seller, making trade efficient, if and only if $\frac{\sigma}{\Delta} \leq 1/3$.

However, when an agent observes ϕ_1 and intermediates trade between the seller and the buyer, trade can be efficient even though $\frac{\sigma}{\Delta} > 1/3$. Specifically, when holding the asset the intermediary is in expectation wealthier from quoting $\phi_1\sigma + \Delta$ rather than $\phi_1\sigma + \sigma + \Delta$ if and only if:

$$\phi_1\sigma + \Delta \geq \frac{1}{2}(\phi_1\sigma + \sigma + \Delta) + \frac{1}{2}\phi_1\sigma,$$

which simplifies to $\frac{\sigma}{\Delta} \leq 1$. Given that, the seller chooses between a price candidate Δ, which is accepted by the intermediary with probability 1, and a price candidate $\sigma + \Delta$, which is accepted by the intermediary with probability 1/2. The seller is in expectation wealthier when quoting Δ rather than $\sigma + \Delta$ if and only if:

$$\Delta \geq \frac{1}{2}(\sigma + \Delta) + \frac{1}{2}\left(\frac{\sigma}{2}\right),$$

which simplifies to $\frac{\sigma}{\Delta} \leq 2/3$.

Hence, in the region where $1/3 < \frac{\sigma}{\Delta} \leq 2/3$, trade is efficient if an intermediary who observes only one of the two factors is involved, but inefficient without an intermediary. The total surplus generated by trade in equilibrium increases from $\frac{3}{4}\Delta$ without an intermediary to Δ with an intermediary. The buyer extracts $\sigma/2$ with an intermediary, which is twice as much as what he would get without an intermediary. Because trade occurs at a low price between the seller and the intermediary, the intermediary is also able to extract a surplus $\sigma/2$.

The seller extracts $\Delta - \sigma$ with the intermediary, but is worse off than without an intermediary when $\frac{\sigma}{\Delta} > 1/3$. When an intermediary is involved, the difference in information quality between counterparties is small enough in both transactions to allow for efficient trade throughout the network. However, this comes at the cost of adding a strategic agent, the intermediary, who captures a share of the surplus and makes the uninformed seller worse off. When trading directly with the expert, the seller has the (socially inefficient) option of selling the asset at a price $\sigma + \Delta$, which the expert accepts to pay with probability $3/4$. With the intermediary, the seller can still sell the asset at a price $\sigma + \Delta$, this time to the intermediary, but the intermediary only accepts to pay this price with probability $1/2$. By making the socially inefficient price quote $\sigma + \Delta$ less attractive to the seller, the intermediary makes him worse off in the region where $1/3 < \frac{\sigma}{\Delta} \leq 2/3$, thus he makes trade more efficient. As a consequence, if allowed the seller would prefer to bypass the intermediary and make an ultimatum offer to the buyer. This deviation would lead to a lower social surplus than if trade goes through the intermediary. The socially efficient trading network therefore centers around a moderately informed intermediary, and it is also *sparse*, in the sense that the seller cannot contact the buyer himself. Alternatively, the expert buyer could commit to ignore any offer coming directly from the uninformed seller, since the buyer is better off when trade goes through a moderately informed intermediary; the expert buyer collects a surplus of $\sigma/2$ when trade goes through the intermediary and is efficient compared to $\sigma/4$ when trade breaks down because no intermediary is involved. The fact that, in practice, it is nearly impossible for retail investors and unsophisticated firms to contact the most sophisticated trading desks directly and bypass the usual middlemen suggests that sparse intermediated networks, or equivalent commitments by sophisticated trading desks, are sensible outcomes of our theory. We discuss in Section 4 the role that ex ante transfers such as payments for order flow can play in ensuring that the socially efficient trading network is Pareto dominant.

Note also that in the region where $1/3 < \frac{\sigma}{\Delta} \leq 2/3$ the surplus the moderately informed agent collects from intermediating trade is greater than the surplus he could collect if he stayed outside the trading network and (credibly) offered to sell his signal to the uninformed agent, in the spirit of Admati and Pfleiderer (1988, 1990). The reason for this result is that a moderately informed intermediary is rewarded for improving trade efficiency, but he also extracts rents from the uninformed agent.

Moreover, replacing the intermediary with a different one who instead observes zero or two factors would eliminate any benefit of intermediation here. Hence, if offered the opportunity to choose his own information set, an intermediary should opt for acquiring more information than the least informed trader and less information than the most informed trader, as it is the only way to extract rents in the intermediation chain.

Finally, note that if trade breaks down despite the involvement of an intermediary, the total surplus that is generated from trade is weakly greater without an intermediary than with one. The intermediary's strategic behavior aimed at appropriating a share of the surplus then becomes an impediment to trade that overpowers the benefits of his involvement that we highlighted so far. This result might help to formalize the role that intermediation chains have played in the recent crisis (i.e., times of high uncertainty), as suggested by Adrian and Shin (2010)

The next special case we consider serves to illustrate that, as the adverse selection problem between the ultimate buyer and seller worsens, more intermediaries may be needed to preserve efficient trade.

Three-Factor Case: Suppose that the asset is worth $v = \phi_1\sigma + \phi_2\sigma + \phi_3\sigma$ to the seller and $v + \Delta$ to the buyer. Without the involvement of intermediaries, we know from eqn. (2) that the seller chooses to quote the efficient price Δ if and only if $\frac{\sigma}{\Delta} \leq \frac{1}{7}$. Proposition 2 also implies that an intermediary who observes one factor realization allows for efficient trade if and only if:

$$\frac{\sigma}{\Delta} \leq \min \quad \left\{ \frac{1}{2^2 - 1}, \frac{1}{2 + \binom{2}{2} - 1} \right\} = 1/3,$$

whereas an intermediary who observes two factor realizations allows for efficient trade if and only if:

$$\frac{\sigma}{\Delta} \leq \min \quad \left\{ \frac{1}{2 - 1}, \frac{1}{2^2 + \binom{1}{2} - 1} \right\} = 2/7.$$

Thus, as in the two-factor case, adding a second layer of transactions to reduce the distance between counterparties' information sets can eliminate entirely the trading inefficiencies that adverse selection imposes. Overall, in the region where $1/7 < \frac{\sigma}{\Delta} \leq 1/3$, trade is efficient if a moderately informed intermediary is involved, but is inefficient without him.

Moreover, involving a second intermediary further extends the region of efficient trade. An intermediation chain in which the seller trades with a first intermediary who observes one factor realization before trading with a second intermediary who observes two factor realizations (including the one the first intermediary observes) before trading with the expert buyer allows for efficient trade if and only if:

$$\frac{\sigma}{\Delta} \leq \min \left\{ \frac{1}{2-1}, \frac{1}{2+\left(\frac{1}{2}\right)-1}, \frac{1}{2+\left(\frac{2}{2}\right)-1} \right\} = 1/2.$$

In the region where $1/3 < \frac{\sigma}{\Delta} \leq 1/2$, trade is thus efficient if two heterogeneously informed intermediaries are involved, but is inefficient with zero or one intermediary.

An important implication of our analysis is that intermediaries should be located within the trading network such that each trader's information set is similar, but not identical, to that of nearby traders. It is socially optimal to have, for example, the least sophisticated intermediaries trading directly with the least informed end-traders, in this case the firm, and the most sophisticated intermediaries trading directly with the most informed end-traders, in this case the expert.

Our paper also highlights that the optimality of specific trading networks greatly depends on the trading frictions that are most relevant in a given context. If efficient trade is impeded by a large information asymmetry related to the value of the asset being traded, our model shows that multiple heterogeneously informed intermediaries may be needed to sustain the social efficiency of trade. If the information asymmetry instead relates to traders' past behavior, Babus (2012) shows that the optimal trading network is centered around a single intermediary who heavily penalizes anyone defaulting on his prior obligations. In Gofman (2011), traders face non-informational bargaining frictions that imply that socially efficient outcomes are easier to achieve when the network is sufficiently dense (although the relationship is not always monotonic). On the other hand, in our model a trading network needs to be sufficiently sparse to sustain efficient trade; otherwise, uninformed parties might privately benefit from trading relationships that reduce social efficiency. (We analyze in the next section the role that order-flow agreements can play in alleviating this problem.) Given that different trading frictions are more relevant in some situations than others, our results and those derived in the papers cited above can help us to understand which type of networks we observe in various contexts.

4 Order-Flow Agreements

We showed in Section 3 that if a social planner wants to maximize the social surplus generated by trade between an uninformed seller and an expert buyer, he may have the uninformed seller trade the asset to a slightly better informed intermediary, who then trades it to another slightly better informed intermediary, and so on until the asset reaches the expert buyer. This intermediation chain will allow trade to occur efficiently, preserving all gains to trade, even in situations where direct trading between the buyer and the seller would be inefficient. We, however, also learned that when an intermediation chain helps to preserve more social surplus than direct trade, the seller may have private incentives to bypass the intermediation chain if allowed. In this section, we characterize order-flow agreements that traders commit to *ex ante* (i.e., before trading takes place) and ensure that no trader involved in an intermediation chain that sustains efficient trade will be tempted to form an alternative trading network. These order-flow agreements will render socially optimal trading networks privately optimal for all traders involved.

Definition 1 (Order-flow agreement) *Consider an economy with a set of traders $\mathbb{T}$. An order-flow agreement Σ between a subset of traders $\mathbb{C} \subseteq \mathbb{T}$ specifies the following objects:*

1. *A collection of directed network links: each trader i in the set $\mathbb{C}$ is exclusively connected to a unique counterparty $j \in \{\mathbb{C} \setminus i\}$ to which trader i quotes an ultimatum price whenever he wishes to sell.*

2. *A collection of ex ante transfers between the traders in the set $\mathbb{C}$.*

A key component of these order-flow agreements are the ex ante transfers that incentivize traders to transact with specific counterparties. In financial markets, these transfers may come in the form of explicit agreements involving cash payments for order flow or soft dollars, or they may be implicit arrangements involving profitable IPO allocations or subsidies on the various other services that intermediaries provide. In fact, there is ample empirical evidence that such "perks" are commonly used by financial intermediaries to compensate traders for their business (see, e.g., Blume 1993, Chordia and Subrahmanyam 1995, Reuter 2006, Nimalendran, Ritter, and Zhang 2007).[11]

Definition 2 (Equilibrium) *An order-flow agreement Σ between a set of traders $\mathbb{C} \subseteq \mathbb{T}$ constitutes an equilibrium if there is no coalition of traders $\mathbb{C}' \subseteq \mathbb{T}$ that can block the agreement, that is, there does not exist an order-flow agreement Σ' that only includes traders in coalition $\mathbb{C}'$ and that makes every trader in $\mathbb{C}'$ weakly better off and at least one trader in $\mathbb{C}'$ strictly better off.*

Consistent with our previous analysis, we are interested in the parameter region in which intermediation chains help to sustain efficient trade. For expositional convenience, we summarize the corresponding conditions as follows.

Condition 1 (Efficient intermediation chain) *The set $\mathbb{T}$ contains traders who are endowed with information sets as described in Section 3, and inequality 2 in Proposition 2 is satisfied.*

We now formally characterize the existence of equilibrium order-flow agreements that support the types of intermediation chains that we introduced in Section 3.

Proposition 3 (Equilibrium order-flow agreements) *If Condition 1 is satisfied, the following results obtain:*

1. *Any order-flow agreement that does not lead to efficient trade is not an equilibrium.*

2. *For any intermediation chain that allows for efficient trade there exists a corresponding order-flow agreement that constitutes an equilibrium.*

Proof. [Part 1] Suppose there exists a set of traders $\mathbb{C} \subseteq \mathbb{T}$ and an order-flow agreement Σ for which trade breaks down with strictly positive probability so that the total surplus across all traders in $\mathbb{C}$ is less than Δ. Further, assume that every trader in $\mathbb{C}$ obtains an ex ante surplus, net of transfers, that is weakly positive (otherwise equilibrium conditions are immediately violated, as

[11] Note that arrangements on cash payments for order flow in equity and option markets are required to be disclosed in advance in Rule 606 reports. Thus, just like in our model, transfers of this type do not vary based on transaction-specific information (i.e., a particular realization of v), although they vary based on the expertise of the traders involved (Easley, Kiefer, and O'Hara 1996). This characterization distinguishes these ex ante transfers from the transfers that occur later as part of the trading process (i.e., the transaction prices p_i^m).

every trader with negative surplus strictly prefers to exit the agreement). Order-flow agreement Σ can be blocked by a coalition of traders $\mathbb{C}' \subseteq \mathbb{T}$: since Condition 1 is satisfied, there exists an order-flow agreement Σ' associated with an intermediation chain that generates efficient trade and preserves a total surplus of Δ. Since the total surplus is greater under agreement Σ' and any trader not involved in Σ collects zero surplus, ex ante transfers can be chosen such that every trader in $\mathbb{C}'$ is strictly better off.

[Part 2] An intermediation chain that allows for efficient trade yields a total ex ante surplus of Δ across all traders. To prove the existence of an order flow agreement that constitutes an equilibrium and supports the efficient intermediation chain consider an order-flow agreement Σ that specifies a set of transfers that imply that all intermediaries involved in agreement Σ obtain zero ex ante surplus (net of transfers), and the ultimate buyer and seller split the total surplus of Δ. Any coalition of traders $\mathbb{C}'$ that attempts to block this order flow agreement would need to include the ultimate buyer and seller, since they are needed to generate a positive surplus from trade. A blocking order-flow agreement Σ' would thus need to make these end traders weakly better off and at least one agent in coalition $\mathbb{C}'$ strictly better off, which is impossible since the ultimate buyer and seller already split the maximum surplus of Δ under agreement Σ and no intermediary would be willing to participate in the blocking order-flow agreement if promised a negative expected surplus.

■

In our model, deal-flow is valuable to any intermediary included in an efficient trading network, since his informational advantage over his counterparty allows him to extract a fraction of the gains to trade Δ. Hence, intermediaries are willing to offer cash payments, or subsidized services, to the ultimate buyer and seller of the asset if these are required concessions for being involved in the trading network. In the proof of Proposition 3, we have focused on order-flow agreements that set the profits of intermediaries, net of these transfers, equal to zero. There, however, may also exist order-flow agreements that provide some intermediaries with strictly positive ex ante surplus. In cases where full efficiency can only be achieved with the involvement of a particular intermediary, equilibrium order-flow agreements will exist such that this important intermediary extracts strictly positive surplus.

5 Other Information Structures

Our main result that chains of intermediaries can facilitate efficient trade was made tractable in our baseline model thanks to a few stylized assumptions about traders' information structures. In this section, we revisit the special cases analyzed in Section 3 and show how the intuition developed so far can be extended to more complex informational settings.

Since in these more complex settings some transactions will involve bargaining games in which a proposer (seller) has private information not known to a responder (buyer), the model will no longer have a unique equilibrium. The goal of the analysis below is to show, under various circumstances, the existence of at least one type of equilibria in which intermediation chains expand the parameter region in which efficient trade is attainable. To ensure that our results are not driven by the multiplicity of equilibria that off-equilibrium beliefs trigger in signaling games, we will first fix off-equilibrium beliefs and then compare the efficiency of trade across various trading networks given those beliefs. We will show that, for a class of beliefs that we argue is reasonable, our original result that intermediation chains facilitate efficient trade is robust to variations in information structures.

Throughout, we will assume that transaction prices quoted in earlier rounds of trade are not observable to traders that were not involved in those rounds. This assumption will streamline our analysis, since an off-equilibrium price quote in one round of trade will trigger belief adjustments for only one trader (that is, the responder in that round of trade). In the context of decentralized markets price opacity appears more suitable than price transparency (see, e.g., Green, Hollifield, and Schürhoff 2007, Duffie 2012), but our results would survive if all traders were to observe the prices quoted in earlier rounds and their beliefs would adjust following a deviation by any informed proposer.

5.1 Two-Sided Asymmetric Information

In Section 2, we introduced an information asymmetry between a buyer and a seller that was one sided. We now show that the intuition developed in our baseline model extends to situations in which both end-traders have private information about the value of the asset. We revisit the two- and three-factor cases analyzed in Section 3 and prove the existence of perfect Bayesian equilibria in which intermediation chains improve trade efficiency just as they did earlier.

Before solving for the conditions for efficient trade throughout a given trading network, we introduce the following Lemma:

Lemma 2 (Efficient trade and pooling equilibria) *The only equilibria in which efficient trade occurs are pooling equilibria in which the proposer does not alter his price quote based on his private information, and this price quote is always accepted by the responder.*

Proof. Suppose there is an equilibrium in which the proposer alters his price quote based on his private information. In such an equilibrium, for trade to be efficient the responder needs to accept all of the proposer's offers. If the proposer anticipates such a response, then he should quote the highest equilibrium price, regardless of his information, contradicting the initial claim. ■

Two-Factor Case, revisited: Recall that in Section 3, we showed that, if the seller is uninformed about v but the buyer observes $\{\phi_1, \phi_2\}$, involving an intermediary who observes one factor allows for efficient trade as long as: $\frac{\sigma}{\Delta} \leq 2/3$. Trade is, however, inefficient without the intermediary whenever $\frac{\sigma}{\Delta} > 1/3$.

Here, we consider instead the case where asymmetric information is two sided, that is, the seller only observes ϕ_1 and the buyer only observes ϕ_2. Both end traders are thus partially informed about v and the trader who makes the ultimatum offer now possesses information his counterparty does not possess. It will greatly simplify our analysis to restrict our attention to off-equilibrium beliefs that have the responder updating the probability that $\phi_1 = 1$ from $1/2$ to μ when quoted by the seller any price higher than the equilibrium price quote. Since efficient trade cannot be sustained, with or without intermediaries, whenever $\mu > 1/2$, we restrict our attention to situations for which $\mu \in [0, \frac{1}{2}]$ and compare the parameter regions that allows for efficient trade in different networks, just as we did when analyzing the baseline model.[12] This class of beliefs allows our equilibrium to satisfy the Intuitive Criterion of Cho and Kreps (1987). In our context, the Intuitive Criterion requires that a buyer ascribes zero probability to any seller type who would be worse off by quoting a higher price regardless of the buyer's actions. Clearly, both seller types would be better off with a higher price should the buyer accept. A natural example for these off-equilibrium beliefs sets $\mu = 1/2$, meaning that a deviation to a higher price quote is uninformative about the proposer's

[12] When $\mu > 1/2$, a seller always finds profitable to quote an infinitesimally higher price than the pooling equilibrium price because it is accepted by the buyer given his beliefs. This profitable deviation implies that no pooling, perfect Bayesian equilibrium exists and trade cannot be efficient according to Lemma 2.

private information. Such off-equilibrium beliefs are particularly reasonable given that any seller would strictly prefer to collect more than the equilibrium price, whenever possible. As we will show though, many other off-equilibrium beliefs μ allow our results to survive qualitatively, but the region over which intermediation chains sustain efficient trade differs.

We know from Lemma 2 that without an intermediary efficient trade is possible if and only if there exists a pooling price that is always accepted by the buyer. We denote the highest pooling price that a buyer always accepts by $\bar{p} = \frac{\sigma}{2} + \Delta$. This price is also the pooling price best able to sustain efficient trade. The buyer believes that any higher price quote coming from the seller implies that $\phi_1 = 1$ with probability $\mu \leq 1/2$. All that is left to check then is that the seller prefers to quote the buyer $\bar{p}$, which is always accepted, rather than $\mu\sigma + \sigma + \Delta$, which is only accepted half the time:

$$\frac{\sigma}{2} + \Delta \geq \frac{1}{2}\left(\mu\sigma + \sigma + \Delta\right) + \frac{1}{2}\phi_1\sigma.$$

This condition is always satisfied as long as: $\frac{\sigma}{\Delta} \leq \frac{1}{1+\mu}$. Trade is inefficient if no intermediary is involved and this inequality is violated.

Now, the counterpart for the two-sided asymmetric information case of the moderately informed intermediary we had in the baseline model is an uninformed intermediary: his involvement splits an information asymmetry of two factors into two transactions that each involve a one-factor informational advantage. Conjecturing that efficient trade occurred in the first transaction, the uninformed intermediary prefers to quote the buyer $\bar{p}$ rather than $\bar{p} + \sigma$ if and only if:

$$\frac{\sigma}{2} + \Delta \geq \frac{1}{2}\left(\frac{\sigma}{2} + \sigma + \Delta\right) + \frac{1}{2}\frac{\sigma}{2},$$

which simplifies to $\frac{\sigma}{\Delta} \leq 1$. Given this, the highest pooling price the uninformed intermediary accepts to pay to the seller is also $\bar{p}$. Any higher price quote would be rejected by the intermediary, given his off-equilibrium beliefs. The seller then prefers to quote $\bar{p}$ rather than holding on to the asset if

$$\frac{\sigma}{2} + \Delta \geq \phi_1\sigma + \frac{\sigma}{2}.$$

This condition is always satisfied as long as: $\frac{\sigma}{\Delta} \leq 1$. Hence, similarly to what happens in the baseline model, as long as $\mu \in (0, \frac{1}{2}]$ there exists a region, i.e., $\frac{1}{1+\mu} < \frac{\sigma}{\Delta} \leq 1$, in which trade is efficient if an intermediary is involved and is inefficient otherwise.

As in Section 3, the two-factor case helped to illustrate how an intermediary can facilitate efficient trade. It, however, takes an environment with at least three factors to observe an intermediation *chain* that sustains efficient trade.

Three-Factor Case, revisited: Instead of the seller being uninformed about v and the buyer observing $\{\phi_1, \phi_2, \phi_3\}$ as in Section 3, we now assume that the seller observes ϕ_1 and the buyer observes $\{\phi_2, \phi_3\}$. The highest pooling price quoted by the seller that is always accepted by the buyer is still $\bar{p}$. The buyer believes that any higher price quote from the seller implies that $\phi_1 = 1$ with probability $\mu \leq 1/2$. We show in Appendix B that efficient trade in this case occurs without intermediaries only if $\frac{\sigma}{\Delta} \leq \frac{1}{2+3\mu}$.

Next, we consider a trading network in which the seller, who observes ϕ_1, trades with an uninformed intermediary who then trades with a second intermediary who observes ϕ_2 and then trades with the buyer, who observes $\{\phi_2, \phi_3\}$. We show in Appendix B that intermediated trade can be efficient as long as: $\frac{\sigma}{\Delta} \leq 2/3$. Thus, for any $\mu \in [0, \frac{1}{2}]$ there exists a region, i.e., $\frac{1}{2+3\mu} < \frac{\sigma}{\Delta} \leq 2/3$, in which trade is inefficient without intermediaries but efficient with a chain of two intermediaries.

5.2 Information Percolation

We now analyze how the intuition developed in our baseline model extends to situations in which traders' information sets are non-nested initially, but information percolates through trade as in Duffie, Malamud, and Manso (2009, 2013). We revisit the three-factor case from Section 3 and prove the existence of perfect Bayesian equilibria in which intermediation chains improve trade efficiency just as they did earlier.

Three-Factor Case, revisited: Recall that in Section 3 we showed that involving two intermediaries, who respectively observe the information sets $\{\phi_1\}$ and $\{\phi_1, \phi_2\}$, between an uninformed seller and a fully informed buyer allows for efficient trade as long as: $\frac{\sigma}{\Delta} \leq 1/2$. Trade is, however, inefficient with one or no intermediary if: $\frac{\sigma}{\Delta} > 1/3$.

In this section, the structure of information sets deviates from what we had initially in that there are two intermediaries who observe *disjoint* sets of factors before trading occurs. Traders, however, learn the information of their respective counterparty after trading has occurred, which is analogous to the notion of information percolation analyzed by Duffie, Malamud, and Manso (2009, 2013).[13]

Specifically, we consider a trading network in which the uninformed seller trades with a first intermediary, who initially observes only ϕ_1, and then trades with a second intermediary, who initially observes only ϕ_2. Finally, the second intermediary trades with the expert buyer. Because information percolates once the two intermediaries have finalized their joint transaction, the second intermediary knows the realizations of factors $\{\phi_1, \phi_2\}$ by the time he quotes a price to the expert. As in the scenario above with two-sided asymmetric information, the bargaining game now involves a proposer (the first intermediary) with private information not known to a responder (the second intermediary) so that the model no longer has a unique equilibrium. The purpose of the current analysis is to show the existence of at least one type of equilibria in which intermediation chains facilitate efficient trade. We conjecture an equilibrium that sustains efficient trade and satisfies the following properties:

- The uninformed seller quotes a price $\bar{p}$ to the first intermediary, who always accepts.
- Regardless of the realization of ϕ_1 he observes, the first intermediary quotes the highest price at which the second intermediary, knowing nothing about the first intermediary's information, always accepts: $\bar{p} = \frac{\sigma}{2} + \Delta$.
- The second intermediary updates the probability that $\phi_1 = 1$ from $1/2$ to $\mu \in [0, \frac{1}{2}]$ when quoted any price higher than $\bar{p}$ by the first intermediary.
- The second intermediary quotes a price $\phi_1\sigma + \phi_2\sigma + \Delta$ to the expert buyer, who always accepts.

In Appendix C, we prove the existence of a perfect Bayesian equilibrium as defined above as long

[13] As in Duffie, Malamud, and Manso (2009, 2013) the traders in our model do not have any reason to refrain from sharing their information with their counterparty once a transaction has been finalized. Sharing information prior to the transaction occurring would, however, not be optimal for informed traders. A prospective seller does not want to share a bad private signal about v prior to the transaction, but he has no reason not to do so once the transaction has been finalized. Unlike Duffie, Malamud, and Manso (2009, 2013), we abstract away from the specific process through which information sharing occurs. Instead, we focus on showing that the efficiency gains that intermediation chains produce with nested information sets survive in an environment with information percolation.

as: $\frac{\sigma}{\Delta} \leq \frac{2}{3+2\mu}$. Nested information sets are thus not necessary for intermediation chains to facilitate efficient trade under asymmetric information. As before, the class of beliefs we assume ensures that our equilibrium satisfies the Intuitive Criterion from Cho and Kreps (1987). However, what is special here is that reasonable off-equilibrium beliefs for which $\mu = 1/2$ also produce a condition for efficient intermediated trade that is identical to the condition we derived in Section 3 when information sets were nested. When $\mu = 1/2$, trade is efficient in the region where $1/3 < \frac{\sigma}{\Delta} \leq 1/2$ if two heterogeneously informed intermediaries are involved, but is inefficient with zero or one intermediary. This example shows that in the presence of information percolation, replacing an intermediation chain with nested information sets by a chain with non-nested information sets may sustain efficient trade in a very similar manner.

5.3 Expert Sellers

The last point we want to highlight in this section is that results similar to those derived in Section 3 can arise when the seller is the expert and the buyer is uninformed. If we allow intermediaries to short sell the asset, those results can be obtained without the complications that arise in signaling games. We revisit the two-factor case to show that conditions on $\frac{\sigma}{\Delta}$ for efficient trade are identical to the conditions we derived earlier. Extending this comparison to an N-factor case with an M-intermediary chain would be straightforward, yet redundant.

Two-Factor Case, revisited: As before, suppose the asset is worth $v = \phi_1\sigma + \phi_2\sigma$ to the seller and $v + \Delta$ to the buyer. However, the seller now observes $\{\phi_1, \phi_2\}$ while the buyer is uninformed about these factors. To eliminate signalling concerns and remain consistent with the analysis in Section 3, the uninformed buyer is assumed to be making an ultimatum offer to the seller. Without an intermediary, the buyer chooses to offer one of three price candidates: (i) 2σ, which is accepted by the seller with probability 1; (ii) σ, which is accepted with probability 3/4; (iii) 0, which is accepted with probability 1/4.

The first price candidate 2σ splits the surplus from trade such that the buyer collects $\Delta - \sigma$ and the seller collects σ. The second price candidate σ produces an expected surplus of $\frac{3}{4}\Delta - \frac{1}{4}\sigma$ for the buyer and $\frac{1}{4}\sigma$ for the seller. The third price candidate produces an expected surplus of $\frac{1}{4}\Delta$

for the buyer and no surplus for the seller. Offering the high price 2σ is thus optimal for the buyer, making trade efficient, if and only if $\frac{\sigma}{\Delta} \leq 1/3$.

However, when an agent observes ϕ_1 and intermediates trade between the seller and the buyer, trade can be efficient even though $\frac{\sigma}{\Delta} > 1/3$. Remember that here we allow the intermediary to sell the asset short, that is, he can accept to sell the asset to the buyer as long as he also buys the asset from the seller. Consistent with the nested information sets assumed in Section 3, the uninformed buyer first makes an offer to purchase the asset from the intermediary who then makes an offer to the seller.

In order to buy the asset from the seller, the intermediary can offer a price $\phi_1\sigma + \sigma$ to the seller, which is always accepted, or a price $\phi_1\sigma$, which is only accepted half the time. Since the buyer makes an ultimatum offer to the intermediary and the intermediary can only accept it if he commits to buy the asset from the seller, trade is efficient as long as the buyer prefers to quote the buyer 2σ, which is always accepted by the intermediary, rather than σ, which is only accepted half the time:

$$\sigma + \Delta - 2\sigma \geq \frac{1}{2}\left(\frac{\sigma}{2} + \Delta - \sigma\right),$$

which simplifies to $\frac{\sigma}{\Delta} \leq 2/3$.

As we can see, although the mechanics of intermediation with short selling are different, the region $1/3 < \frac{\sigma}{\Delta} \leq 2/3$ for which trade can only be efficient if a moderately informed intermediary is involved is identical to the corresponding region derived in Section 3 when the expert was a buyer instead of a seller.

6 Conclusion

This paper shows how chains of heterogeneously informed intermediaries can help to alleviate adverse selection problems that impede efficient trading between asymmetrically informed agents. Complex trading networks that sequentially involve several intermediaries may be the socially optimal response to information asymmetries as reallocating a large adverse selection problem over multiple transactions reduces agents' incentives to inefficiently limit trade when facing their better informed counterparties. Thus, greater information asymmetries require longer intermediation chains to sustain efficient trade, consistent for example with Li and Schürhoff (2014) who show that unrated municipal bonds are typically traded through longer intermediation chains than rated municipal bonds (which arguably are less likely to be associated with large adverse selection problems). Moreover, if market participants implement efficient networks, our theory predicts that larger information asymmetries will be associated with more trading being observed, which contrasts with the conventional wisdom that empirically, large information asymmetries should be associated with low trading volume (as in Akerlof 1970). Finally, because informed intermediaries extract rents in a socially optimal trading network, they are willing to offer transfers such as cash payments, or subsidies on services they perform, to other traders in exchange for their order flow. This result might help to inform the current policy debate on the use of order-flow agreements in financial markets.

Appendix A: Proofs

Lemma 3 (Necessary and sufficient condition for efficient trade) *Given that trade is efficient in all subsequent transactions, trader m finds optimal to quote p_0^m rather than any other price if and only if he prefers to quote p_0^m over p_1^m.*

Proof. Consider a situation in which trader m currently holds the asset and wants to sell it to trader $m+1$. Trader m knows that out of the N_m factors ϕ_n he observes, G_m realizations have a value of 1. Similarly, trader $m+1$ knows that out of the N_{m+1} factors ϕ_n he observes, G_{m+1} realizations have a value of 1. Assume that whenever trader $m+1$ acquires the asset, subsequent trading is efficient, which requires that all subsequent traders $k \in \{m+1, m+2, ..., M\}$ charge prices:

$$p_0^k = G_k \sigma + \Delta,$$

which maximize trade probability. Trader m then chooses to quote one of $(N_{m+1} - N_m + 1)$ price candidates, defined as:

$$p_i^m = (G_m + i)\,\sigma + \Delta, \quad i \in \{0, ..., N_{m+1} - N_m\}.$$

The weakly better informed trader $m+1$ only accepts to pay a price p_i^m if $G_{m+1}\sigma + \Delta \geq p_i^m$, which occurs with probability π_i^m.

Trader m prefers quoting p_i^m over p_{i+1}^m if and only if:

$$\begin{aligned}
& \pi_i^m p_i^m + (1 - \pi_i^m)\, E\left[v | G_{m+1} < G_m + i\right] \geq \pi_{i+1}^m p_{i+1}^m + \left(1 - \pi_{i+1}^m\right) E\left[v | G_{m+1} < G_m + i + 1\right] \\
\Leftrightarrow \quad & \pi_i^m p_i^m - \pi_{i+1}^m p_{i+1}^m \geq \left(1 - \pi_{i+1}^m\right) E\left[v | G_{m+1} < G_m + i + 1\right] - (1 - \pi_i^m)\, E\left[v | G_{m+1} < G_m + i\right] \\
\Leftrightarrow \quad & (\pi_i^m - \pi_{i+1}^m)\left[(G_m + i)\,\sigma + \Delta\right] - \pi_{i+1}^m \sigma \geq \left(\pi_i^m - \pi_{i+1}^m\right)(G_m + i)\sigma \\
\Leftrightarrow \quad & \frac{\sigma}{\Delta} \leq \frac{\pi_i^m - \pi_{i+1}^m}{\pi_{i+1}^m}.
\end{aligned} \tag{3}$$

When the probability distribution that characterizes the information asymmetry between traders m and $m+1$ is such that the (discrete) hazard rate (i.e., the RHS in (3)) reaches its global minimum at $i = 0$, trader m quotes p_0^m if and only if he prefers to quote p_0^m over p_1^m.[14] The binomial distribution has a (discrete) hazard rate that reaches its global minimum at $i = 0$: the probability mass function $\pi_i^m - \pi_{i+1}^m$ is minimized at the two extremes of the distribution, that is, at $i = 0$ and at $i = N_{m+1} - N_m - 1$ and the complementary cumulative distribution function π_{i+1}^m is decreasing in i. ■

Appendix B: Efficient Trade with Two-Sided Asymmetric Information

In this scenario, we assume that the seller observes ϕ_1 and the buyer observes $\{\phi_2, \phi_3\}$. The highest pooling price quoted by the seller that is always accepted by the buyer is still $\bar{p}$. Given his off-equilibrium beliefs, any higher price quote would be perceived by the buyer as meaning that $\phi_1 = 1$ with probability $\mu \leq 1/2$. Hence, the two conditions that need to be satisfied for efficient trade to occur without intermediaries are:

$$\frac{\sigma}{2} + \Delta \geq \frac{3}{4}(\mu\sigma + \sigma + \Delta) + \frac{1}{4}\sigma,$$

which simplifies to $\frac{\sigma}{\Delta} \leq \frac{1}{2+3\mu}$, and

$$\frac{\sigma}{2} + \Delta \geq \frac{1}{4}(\mu\sigma + 2\sigma + \Delta) + \frac{1}{2}2\sigma + \frac{1}{4}\sigma,$$

which simplifies to $\frac{\sigma}{\Delta} \leq \frac{3}{5+\mu}$. When $\mu \geq 0$, the first condition is more restrictive than the second one and efficient trade is thus possible without intermediaries only if $\frac{\sigma}{\Delta} \leq \frac{1}{2+3\mu}$.

Next, we consider a trading network in which the seller, who observes ϕ_1, trades with an uninformed intermediary, who then trades with a second intermediary who observes ϕ_2 and then trades with the buyer, who observes $\{\phi_2, \phi_3\}$. Conjecturing that efficient trade occurred in the first two transactions, the second intermediary prefers to quote the buyer $\bar{p} + \phi_2\sigma$ rather than $\bar{p} + \phi_2\sigma + \sigma$ if and only if:

$$\frac{\sigma}{2} + \phi_2\sigma + \Delta \geq \frac{1}{2}\left(\frac{\sigma}{2} + \phi_2\sigma + \sigma + \Delta\right) + \frac{1}{2}\left(\frac{\sigma}{2} + \phi_2\sigma\right),$$

[14] More generally, a hazard rate function is defined as $\frac{pmf(x)}{1-cdf(x)}$, where pmf and cdf respectively denote the probability mass function and the cumulative distribution function.

which simplifies to $\frac{\sigma}{\Delta} \leq 1$. Given that, the first intermediary prefers to quote $\bar{p}$ rather than $\bar{p}+\sigma$ to the second intermediary if and only if:

$$\frac{\sigma}{2} + \Delta \geq \frac{1}{2}\left(\frac{\sigma}{2} + \sigma + \Delta\right) + \frac{1}{2}\sigma,$$

which simplifies to $\frac{\sigma}{\Delta} \leq 2/3$. Given that, the highest pooling price that the uninformed intermediary will accept to pay to the seller is also $\bar{p}$. Any higher price quote would be rejected by the uninformed intermediary, given his off-equilibrium beliefs. All that is left to check then is that the seller prefers to quote $\bar{p}$ rather than holding on to the asset, even if $\phi_1 = 1$:

$$\frac{\sigma}{2} + \Delta \geq 2\sigma,$$

which simplifies to $\frac{\sigma}{\Delta} \leq 2/3$.

Appendix C: Efficient Trade with Information Percolation

In this scenario, we consider a trading network in which the uninformed seller trades with a first intermediar who observes ϕ_1 and then trades with a second intermediary, who observes ϕ_2. Finally, the second intermediary trades with the expert buyer. We conjecture a perfect Bayesian equilibrium in which trade is efficient and the following properties apply:

- The uninformed seller quotes a price $\bar{p}$ to the first intermediary, who always accepts.
- Regardless of the realization of ϕ_1 he observes, the first intermediary quotes the highest price at which the second intermediary, knowing nothing about the first intermediary's information, always accepts: $\bar{p} = \frac{\sigma}{2} + \Delta$.
- The second intermediary updates the probability that $\phi_1 = 1$ from $1/2$ to $\mu \in [0, \frac{1}{2}]$ when quoted any price higher than $\bar{p}$ by the first intermediary.
- The second intermediary quotes a price $\phi_1\sigma + \phi_2\sigma + \Delta$ to the expert buyer, who always accepts.

To prove the existence of such equilibrium, we first need to analyze the last stage of trading between the second intermediary and the expert, which is identical to the last stage of trading in the two-factor and three-factor cases from Section 3. If $\frac{\sigma}{\Delta} \leq 1$, the second intermediary finds optimal to quote a price $\phi_1\sigma + \phi_2\sigma + \Delta$ to the expert, which he always accepts.

Trading between the two intermediaries is slightly more complex to analyze, since information sets are non-nested. The first intermediary quotes a price, after observing ϕ_1, to the second intermediary who only observes ϕ_2. Given the beliefs assumed, the most attractive deviation by the first intermediary from the conjectured equilibrium action is to quote a price $\mu\sigma + \sigma + \Delta$, which is accepted by the second intermediary only if $\phi_2 = 1$. Such deviation is dominated by the equilibrium strategy of quoting $\bar{p}$, even if $\phi_1 = 1$, as long as:

$$\begin{aligned} \frac{\sigma}{2} + \Delta &\geq \frac{1}{2}(\mu\sigma + \sigma + \Delta) + \frac{1}{2}\left(\sigma + \frac{\sigma}{2}\right) \\ \Leftrightarrow \frac{\sigma}{\Delta} &\leq \frac{2}{3 + 2\mu}. \end{aligned}$$

Further, collecting $\bar{p}$ also dominates non-participation for the first intermediary, as long as $\frac{\sigma}{\Delta} \leq \frac{1}{\frac{1}{2}+\phi_1}$. When $\frac{\sigma}{\Delta} \leq \frac{2}{3+2\mu}$, quoting $\bar{p}$ is thus always the equilibrium strategy for the first intermediary in this stage.

Finally, the seller can quote $\bar{p}$ to the first intermediary, which is accepted with probability 1, but he might also consider quoting a higher price. Since the first intermediary plans on subsequently quoting $\bar{p}$, regardless of his information, no such higher price quote by the seller can sustain trade with positive probability. The seller thus chooses to quote $\bar{p}$ as long as it dominates non-participation:

$$\begin{aligned} \frac{\sigma}{2} + \Delta &\geq \frac{3}{2}\sigma \\ \Leftrightarrow \frac{\sigma}{\Delta} &\leq 1. \end{aligned}$$

Overall, all the conditions required for the conjectured perfect Bayesian equilibrium to exist are verified if and only if $\frac{\sigma}{\Delta} \leq \frac{2}{3+2\mu}$.

References

Admati, Anat R., and Paul Pfleiderer, 1988, "Selling and Trading on Information in Financial Markets," *American Economic Review* 78, 96-103.

Admati, Anat R., and Paul Pfleiderer, 1990, "Direct and Indirect Sale of Information," *Econometrica* 58, 901-928.

Adrian, Tobias, and Hyun Song Shin, 2010, "The Changing Nature of Financial Intermediation and the Financial Crisis of 2007-2009," *Annual Review of Economics* 2, 603-618.

Akerlof, George A., 1970, "The Market for "Lemons": Quality Uncertainty and the Market Mechanism," *Quarterly Journal of Economics* 84, 488-500.

Babus, Ana, 2012, "Endogenous Intermediation in Over-the-Counter Markets," Working Paper, Imperial College London.

Bank of International Settlements, 2013, "Triennial Central Bank Survey — Foreign Exhange Turnover in April 2013: Preliminary Global Results," Monetary and Economic Department, Basel, Switzerland.

Biais, Bruno, and Augustin Landier, 2013, "The (ir)resistible rise of agency rents," Working Paper, Toulouse School of Economics.

Biglaiser, Gary, 1993, "Middlemen as Experts," *RAND Journal of Economics* 24, 212-223.

Blume, Marshall E., 1993, "Soft Dollars and the Brokerage Industry," *Financial Analysts Journal* 49, No. 2, 36-44.

Bolton, Patrick, Tano Santos, and Jose A. Scheinkman, 2012, "Cream Skimming in Financial Markets," Working Paper, Columbia University.

Cetorelli, Nicola, Benjamin H. Mandel, and Lindsay Mollineaux, 2012, "The Evolution of Banks and Financial Intermediation: Framing the Analysis," *FRBNY Economic Policy Review*, July Issue, 1-12.

Chakraborty, Archishman, and Bilge Yilmaz, 2011, "Adverse Selection and Convertible Bonds," *Review of Economic Studies* 78, 148-175.

Cho, In-Koo, and David M. Kreps, 1987, "Signalling Games and Stable Equilibria," *Quarterly Journal of Economics* 102, 381-413.

Chordia, Tarun, and Avanidhar Subrahmanyam, 1995, "Market Making, the Tick Size, and Payment-for-Order Flow: Theory and Evidence," *Journal of Business* 68, 543-575.

DeMarzo, Peter M., 2005, "The Pooling and Tranching of Securities: A Model of Informed Intermediation," *Review of Financial Studies* 18, 1-35.

Diamond, Douglas W., 1984, "Financial Intermediation and Delegated Monitoring," *Review of Economic Studies* 51, 393-414.

Duffie, Darrell, 2012, *Dark Markets: Asset Pricing and Information Transmission in Over-the-Counter Markets*, Princeton: Princeton University Press.

Duffie, Darrell, Nicolae Gârleanu, and Lasse Heje Pedersen, 2005, "Over-the-Counter Markets," *Econometrica* 73, 1815-1847.

Duffie, Darrell, Semyon Malamud, and Gustavo Manso, 2009, "Information Percolation with Equilibrium Search Dynamics," *Econometrica* 77, 1513-1574.

Duffie, Darrell, Semyon Malamud, and Gustavo Manso, 2013, "Information Percolation in Segmented Markets," Working Paper, Stanford University.

Easley, David, Nicholas M. Kiefer, and Maureen O'Hara, 1996, "Cream-Skimming or Profit-Sharing? The Curious Role of Purchased Order Flow," *Journal of Finance* 51, 811-833.

Farboodi, Maryam, 2014, "Intermediation and Voluntary Exposure to Counterparty Risk," Working Paper, University of Chicago.

Foster, F. Douglas, and S. Viswanathan, 1993, "Variations in Trading Volume, Return Volatility, and Trading Costs: Evidence on Recent Price Formation Models," *Journal of Finance* 48, 187-211.

Glode, Vincent, Richard C. Green, and Richard Lowery, 2012, "Financial Expertise as an Arms Race," *Journal of Finance* 67, 1723-1759.

Glode, Vincent, and Richard Lowery, 2013, "Informed Trading and High Compensation in Finance," Working Paper, University of Pennsylvania.

Glosten, Lawrence R., and Lawrence E. Harris, 1988, "Estimating the Components of the Bid/Ask Spread," *Journal of Financial Economics* 21, 123-142.

Glosten, Lawrence R., and Paul R. Milgrom, 1985, "Bid, Ask, and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders," *Journal of Financial Economics* 14, 71-100.

Gofman, Michael, 2011, "A Network-Based Analysis of Over-the-Counter Markets," Working Paper, University of Wisconsin - Madison.

Gould, John F., and Allan W. Kleidon, 1994, "Market Maker Activity on NASDAQ: Implications for Trading Volume," *Stanford Journal of Law, Business & Finance* 1, 1-17.

Green, Richard C., Burton Hollifield, and Norman Schürhoff, 2007, "Financial Intermediation and the Costs of Trading in an Opaque Market," *Review of Financial Studies* 20, 275-314.

Hansch, Oliver, Narayan Y. Naik, and S. Viswanathan, 1998, "Do Inventories Matter in Dealership Markets? Evidence from the London Stock Exchange," *Journal of Finance* 53, 1623-1656.

Hasbrouck, Joel, and George Sofianos, 1993, "The Trades of Market Makers: An Empirical Analysis of NYSE Specialists," *Journal of Finance* 48, 1565-1593.

Ho, Thomas, and Hans R. Stoll, 1983, "The Dynamics of Dealer Markets under Competition," *Journal of Finance* 38, 1053-1074.

Hollifield, Burton, Artem Neklyudov, and Chester Spatt, 2014, "Bid-Ask Spreads and the Pricing of Securitizations: 144a vs. Registered Securitizations," Working Paper, Carnegie Mellon University.

Jovanovic, Boyan, and Albert J. Menkveld, 2012, "Middlemen in Limit-Order Markets," Working Paper, New York University.

Keim, Donald B., and Ananth Madhavan, 1996, "The Upstairs Market for Large-Block Transactions: Analysis and Measurement of Price Effects," *Review of Financial Studies* 9, 1-36.

Kroszner, Randall S., and William Melick, 2009, "The Response of the Federal Reserve to the Recent Banking and Financial Crisis," Working Paper, University of Chicago.

Kyle, Albert S., 1985, "Continuous Auctions and Insider Trading," *Econometrica* 53, 1315-1335.

Li, Yiting, 1998, "Middlemen and Private Information," *Journal of Monetary Economics* 42, 131-159.

Li, Dan, and Norman Schürhoff, 2014, "Dealer Networks," Working Paper, Swiss Finance Institute.

Lyons, Richard K., 1996, "Foreign Exchange Volume: Sound and Fury Signifying Nothing?," in *The Microstructure of Foreign Exchange Markets*, National Bureau of Economic Research, 183-208.

Madhavan, Ananth, and Seymour Smidt, 1993, "An Analysis of Changes in Specialist Inventories and Quotations," *Journal of Finance* 48, 1595-1628.

Malamud, Semyon, and Marzena Rostek, 2013, "Decentralized Exchanges," Working Paper, Swiss Finance Institute.

Manaster, Steven, and Steven C. Mann, 1996, "Life in the Pits: Competitive Market Making and Inventory Control," *Review of Financial Studies* 9, 953-975.

Morris, Stephen, and Hyun Song Shin, 2012, "Contagious Adverse Selection," *American Economic Journal: Macroeconomics* 4, 1-21.

Murphy, Kevin M., Andrei Schleifer, and Robert W. Vishny, 1991, "The Allocation of Talent: Implications for Growth," *Quarterly Journal of Economics* 106, 503-530.

Myerson, Roger B., and Mark A. Satterthwaite, 1983, "Efficient Mechanisms for Bilateral Trading," *Journal of Economic Theory* 29, 265-281.

Neklyudov, Artem V., 2013, "Bid-Ask Spreads and the Decentralized Interdealer Markets: Core and Peripheral Dealers," Working Paper, University of Lausanne.

Nimalendran, M., Jay R. Ritter, and Donghang Zhang, 2007, "Do Today's Trades Affect Tomorrow's IPO Allocations?," *Journal of Financial Economics* 84, 87-109.

Pozsar, Zoltan, Tobias Adrian, Adam Ashcraft, and Hayley Boesky, 2013, "Shadow Banking," *FRBNY Economic Policy Review*, December Issue, 1-16.

Philippon, Thomas, 2010, "Engineers vs. Financiers: Should the Financial Sector be Taxed or Subsidized," *American Economic Journal: Macro* 2, 158-182.

Reiss, Peter C., and Ingrid M. Werner, 1998, "Does Risk Sharing Motivate Interdealer Trading?," *Journal of Finance* 53, 1657-1703.

Reuter, Jonathan, 2006, "Are IPO Allocations for Sale? Evidence from Mutual Funds," *Journal of Finance* 61, 2289-2324.

Rubinstein, Ariel, and Asher Wolinsky, 1987, "Middlemen," *Quarterly Journal of Economics* 102, 581-594.

Seppi, Duane J., 1990, "Equilibrium Block Trading and Asymmetric Information," *Journal of Finance* 45, 73-94.

Stoll, Hans R., 1989, "Inferring the Components of the Bid-Ask Spread: Theory and Empirical Tests," *Journal of Finance* 44, 115-134.

Shin, Hyun Song, 2003, "Disclosures and Asset Returns," *Econometrica* 71, 105-133.

Townsend, Robert M., 1978, "Intermediation with Costly Bilateral Exchange," *Review of Economic Studies* 45, 417-425.

Viswanathan, S., and James J.D. Wang, 2004, "Inter-Dealer Trading in Financial Markets," *Journal of Business* 77, 1-54.

Weller, Brian, 2013, "Liquidity and High Frequency Trading," Working Paper, University of Chicago.

Yang, Ming, 2013, "Optimality of Debt under Flexible Information Acquisition," Working Paper, Duke University.

Yavaş, Abdullah, 1994, "Middlemen in Bilateral Search Markets," *Journal of Labor Economics* 12, 406-429.

Stress Tests and Information Disclosure*

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Abstract

We study an optimal disclosure policy of a regulator who has information about banks' ability to overcome future liquidity shocks. We focus on the following trade-off: Disclosing some information may be necessary to prevent a market breakdown, but disclosing too much information destroys risk-sharing opportunities (Hirshleifer effect). We find that during normal times, no disclosure is optimal, but during bad times, partial disclosure is optimal. We characterize the optimal form of this partial disclosure. We also relate our results to the debate on the disclosure of stress test results.

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1 Introduction

In the new era of financial regulation following the crisis of 2008, central banks around the world will conduct periodic stress tests for financial institutions to assess their ability to withstand future shocks. A key question that occupies policymakers and bankers is whether the results of the stress tests should be disclosed and, if so, at what level of detail. The debate over this question is summarized in an article in the *Wall Street Journal* from March 2012. In this article, Fed Governor Daniel Tarullo expresses support for wide disclosure, saying that "the disclosure of stress-test results allows investors and other counterparties to better understand the profiles of each institution." On the other hand, the Clearing House Association expresses the concern that making the additional information public "could have unanticipated and potentially unwarranted and negative consequences to covered companies and U.S. financial markets."[1]

A classic concern about disclosure in the economics literature is based on the Hirshleifer effect (Hirshleifer, 1971). According to the Hirshleifer effect, greater disclosure might decrease welfare because it reduces risk-sharing opportunities for economic agents. This is indeed a relevant concern in the context of banks and stress tests. A large literature (e.g., Allen and Gale, 2000) studies risk-sharing arrangements among banks. If banks are exposed to random liquidity shocks, they will create arrangements among themselves or with outside markets to insure against such shocks. If more information about the state of each individual bank and its ability to withstand future shocks is publicly disclosed, then such risk-sharing opportunities will be limited, generating a welfare loss.

While this concern may provide credible content to the "unwarranted and negative consequences" referred to in the above quote from the Clearing House Association, it is hard to deny that greater disclosure that "allows investors and other counterparties

[1] See "Lenders Stress over Test Results," *Wall Street Journal*, March 5, 2012.

to better understand the profiles of each institution" appears to be crucial at times. In particular, as was clear during the recent financial crisis, when aggregate conditions seem bleak, the lack of disclosure might lead to a breakdown in financial activity. In the context of risk sharing and insurance, if the aggregate state of the financial sector is perceived to be weak, banks would not be able to insure themselves against undesirable outcomes (see, e.g., Leitner, 2005). In this case, some disclosure on certain banks might be necessary to enable some risk sharing and its welfare-improving effects.

In this paper, we study a model to analyze these forces and provide guidance for optimal disclosure policy in light of these forces. In the model, financial institutions suffer a loss if their future capital falls below a certain level. Part of the future capital of the financial institution can be forecasted based on current analysis and will become clear to policymakers conducting stress tests. However, there are also future shocks that cannot be forecasted with such an analysis. Financial institutions can engage in risk-sharing arrangements to guarantee that their capital does not fall below the critical level.

These risk-sharing arrangements work well if the overall state of the financial industry is perceived to be strong. In this case, no disclosure by the regulator is needed. Consistent with the Hirshleifer effect, disclosure can be even harmful because it prevents optimal risk-sharing arrangements from taking place. However, if, on average, banks are perceived to have capital below the critical level, then risk-sharing arrangements that insure them against falling below that level cannot arise without some disclosure. In this case, partial disclosure emerges as the optimal solution.

To study optimal disclosure rules in bad times, we distinguish between two different cases. First, we consider an environment where the information discovered by the regulator in the stress test is not already known to the bank. This is a reasonable assumption if the information involves assessment of bank exposure to aggregate conditions or to the state of other banks, and those are known to the regulator, who analyzes many banks, and not to the individual banks themselves. In this case, we show that it is optimal to create two scores – a high score and a low score – and to give the high score to a group of banks whose average forecastable capital is equal to the critical level, and a low scores to other banks. This is similar to the Bayesian persuasion solution proposed by Kamenica and Gentzkow (2011).

By providing disclosure that separates some bad banks from the others, the regulator enables risk sharing among the remaining banks. Importantly, for this to work, the regulator must not provide too much information. It is sufficient to use only two scores and classify banks as "good" or "bad." Providing more detailed information about the "bad" banks does not hurt, but the regulator must not provide more information about "good" banks. In particular, within the group of "good" banks, there are some "bad" banks as well; pooling these banks together enables risk sharing.

Interestingly, the disclosure rule is not necessarily monotone; i.e., it is not always the case that banks below a certain threshold are classified as "bad" and others are classified as "good." There is a gain and a cost from including a bank in the "good" group. The gain is enabling the bank to participate in the risk sharing, preventing a welfare-decreasing drop in capital. The cost is that placing the bank in the "good" group takes resources, thereby preventing other banks from being in that group. The allocation of banks into the "good" group depends on the gain-to-cost ratio, and this does not always generate a monotone rule; it depends on the distribution of shocks that banks are exposed to. We provide conditions under which the disclosure rule is monotone.

The second environment we consider is one where the information discovered by the regulator in the stress test is known to the bank itself but not to the outside market. In this case, pooling banks into two groups will not generally work. Banks whose forecastable level of capital is significantly above the critical level will refuse to participate in a risk-sharing arrangement with a group whose average forecastable capital is just at the critical level. Hence, in this case, the optimal disclosure rule has multiple scores. As before, one score is reserved for banks that are revealed to be below the critical capital level, and these banks are shunned from risk-sharing arrangements. Other scores pool together banks below the critical level with a bank above the critical level to enable risk sharing. Different scores are required to accommodate the different reservation utilities of different banks above the critical level of capital.

Interestingly, in this environment, non-monotonicity becomes a general feature of optimal disclosure rules. When considering banks below the critical level of capital, it turns out that the stronger ones will be pooled with a bank whose level of capital is only slightly above the critical level (hence receiving a moderate score), while the weaker ones will be pooled with a bank whose level of capital is significantly above the critical level (hence receiving a high score). As we show in this paper, the increase in cost from pooling with a moderately strong bank to pooling with a very strong bank is not significant for the weakest banks but is significant for the moderately weak banks, and this leads to the non-monotonicity result.

In summary, our paper generates the following results about optimal disclosure rules. First, no disclosure is optimal during good times, but partial disclosure is optimal during bad times. Second, partial disclosure takes the form of different scores pooling together banks of different levels of strength. The number of scores increases as we move from a case in which banks do not already have the information revealed in the stress test to the case in which they do possess this information. Third, non-monotonicity appears to be a pervasive feature of optimal disclosure rules, such that a given score pools together strong banks with weak banks.

1.1 Related literature

The literature on disclosure of regulatory information is reviewed in a recent paper by Goldstein and Sapra (2012), which highlights the disadvantages of disclosure.

Morris and Shin (2002) show that disclosure might be bad if economic agents share strategic complementarities and wish to act like each other even though it is not socially optimal. Providing a public signal then makes them place a too large weight on it because it provides information not only about fundamentals but also about what others know about the fundamentals. However, Angeletos and Pavan (2007) show that this conclusion may not hold when agents share strategic substitutes or when coordination is socially desirable. Leitner (2012) shows that disclosing too much information may reduce the regulator's ability to extract information about complex contracts that banks enter with one another. In his setting, it is optimal to reveal partial information. The regulator should set a position limit for each bank and reveal only whether the bank has reached its limit; however, the regulator should not reveal the exact position that the bank has entered. The idea that disclosing information may reduce the regulator's ability to collect information from banks also appears in Prescott (2008). Bond and Goldstein (2012) show that disclosure of information by the government to the market might harm the government's ability to learn from the market. Hence, the government may want to disclose information only on variables on which it cannot learn from the market. Increased disclosure might also be harmful due to the adverse effect it might have on the ex-ante incentives of bank managers, as in the traditional corporate-finance literature emphasizing the tension between ex-post and ex-ante optimal actions (e.g., Burkart, Gromb, and Panunzi, 1997). Our paper analyzes a different tradeoff involving risk-sharing opportunities, which are at the heart of financial activity.

In a related paper, Lizzeri (1999) studies the optimal disclosure policy of an intermediary who is hired by a firm to certify the quality of its products.[2] Lizzeri (1999) shows that a monopolist intermediary may choose to restrict the flow of information and reveal only the minimum information that is required for an efficient exchange.

[2] See also Kartasheva and Yilmaz (2012), who extend Lizzeri's framework by adding different outside options for firms as well as information asymmetries among potential buyers.

Disclosing less information allows the intermediary to extract more rents from firms that are being rated. Instead, in our setting, providing less information allows for better risk sharing.

There is also an extensive literature that studies information disclosure by firms, particularly whether the regulator should mandate firms to disclose information.[3] Our paper contributes to this literature by illustrating a case in which the regulator would like to restrict information flow from firms. A strong firm ignores the fact that revealing information destroys risk-sharing opportunities for weak firms, but the regulator takes this negative externality into account.

In a different context, Marin and Rahi (2000) provide a theory of market incompleteness, which is based on the tradeoff between adverse selection and the Hirshleifer effect. Adverse selection favors an increase in the number of securities because it reduces information asymmetries among agents. The Hirshleifer effect favors a reduction in the number of securities. Our paper does not talk about security design but instead discusses how the regulator should pool banks into groups to enable risk sharing. Because the utility function in our setting exhibits some convexity (a bank suffers a loss if its capital falls below a certain level), two groups may be necessary even when banks do not have private information. When banks have private information, more groups are necessary to accommodate the different reservation utilities of banks above the critical level.

Finally, the idea that risk-sharing arrangements may break down when aggregate conditions are bleak relates to Leitner (2005). He shows that in this case, it is optimal for banks to remain unlinked rather than form a financial network. In one interpretation of our model, we show how the disclosure policy affects the financial networks that banks form.

[3] A partial list of this literature includes Grossman (1981), Diamond (1985), Fishman and Hagerty (1990, 2003), and Admati and Pfleiderer (2000).

2 A model

2.1 The bank

There are three dates $t = 0, 1, 2$. A bank has an asset that yields a random cash flow at date 1 and no cash flows afterward. This cash flow is the sum of two random variables $\tilde{\theta}$ and $\tilde{\varepsilon}$, where $\tilde{\theta}$ is referred to as the bank's type and $\tilde{\varepsilon}$ is the bank's idiosyncratic risk, which is independent of its type. At date 0, the bank can sell the asset in a perfectly competitive market for an amount x, which will be derived endogenously. The amount of cash available for the bank at date 1, which we denote by z, is therefore $z = \tilde{\theta} + \tilde{\varepsilon}$ if the bank keeps the asset, and $z = x$ if the bank sells the asset. Everyone is risk neutral, and the risk-free rate is normalized to be zero percent; therefore, x equals the expected value of the asset $\tilde{\theta} + \tilde{\varepsilon}$, conditional on the information available to the market.

The bank's date-2 payoff is:

$$R(z) = \begin{cases} z & \text{if } z < 1 \\ z + r & \text{if } z \geq 1. \end{cases} \tag{1}$$

This payoff function is a reduced form to capture the general idea that banks suffer a loss when their cash holdings fall below some threshold. The payoff function can also represent a project that yields a positive net present value $r > 0$ but requires a minimum level of investment. For various reasons (e.g., projects cash flows are nonverifiable), the bank cannot finance the project if it does not have sufficient cash in hand. For convenience, we stick to the project interpretation, but the reader can think of other interpretations.

The bank acts to maximize its expected payoff at $t = 2$: $E\left[R(z)\right]$. As will be clear later, this provides incentives for banks to sell their assets in the financial market for an amount of at least one dollar. This is an insurance to guarantee that the bank can later make the investment. More generally, selling the asset can be thought of as engaging in a risk-sharing arrangement.[4]

The random variables $\tilde{\theta}$ and $\tilde{\varepsilon}$ are drawn at date 0, and we denote their realizations by θ and ε, respectively. The bank's type $\tilde{\theta}$ is drawn from a finite set $\Theta \subset \mathbb{R}$ according to a probability distribution function $p(\theta) = \Pr(\tilde{\theta} = \theta)$. The idiosyncratic risk $\tilde{\varepsilon}$ is drawn from a cumulative distribution function F that satisfies $E(\tilde{\varepsilon}) = 0$; for simplicity, we assume that F is continuous. The probability structure (i.e., the functions p and F) is common knowledge.

The planner observes θ. The market observes neither θ nor ε. As for the bank, we focus on two cases:

(1) The bank observes neither θ nor ε.

(2) The bank observes θ but not ε.

The first case captures the idea that the government may have some information advantage relative to banks. This is a plausible assumption when asset values depend on future government actions or when asset values depend on interactions among banks, and the government's ability to collect information from multiple banks allows it to come up with better estimates. The second case captures the idea that the government and banks share the same information, which is unobservable to other market participants. For example, the bank may know its ability to withstand future liquidity shocks, and the government can find out this information by conducting stress tests.

Denote the lowest type by $\theta_{\min}$ and the highest type by $\theta_{\max}$. We assume that $\theta_{\max} > 1$, so if information on θ were publicly available, at least some types could sell their assets for more than one dollar and invest in their projects. We also assume that:

[4] We rule out partial insurance in which a bank with type $\theta < 1$ sells its asset for a price 1, which is paid with probability θ (i.e., the bank transfers the asset with probability 1 but receives payment with probability that is less than 1). This can be motivated by assuming that banks enter risk-sharing arrangements by forming links as in Leitner (2005). In his model, the bank's investment can succeed only if all the banks to which it is linked invest as well; hence, helping just a fraction of the banks in the network does not help.

Assumption 1: $F(1-\theta_{\min}) < 1$ and $F(1-\theta_{\max}) > 0$.

This implies that for any type realization there is a positive probability that the asset cash flow will be more than 1; but there is also a positive probability that the asset cash flow will be less than 1.

2.2 Disclosure rules

The planner's problem is to choose a disclosure rule, as defined below, to maximize total surplus, taking as given the effect of disclosure on the bank's ability to sell its asset for at least one dollar. Since the market breaks even on average, maximizing total surplus is the same as maximizing the bank's expected utility.

Formally, a *disclosure rule* is a set of "scores" S and a function that maps each type to a distribution over scores. Since Θ is assumed to be finite, we also assume that S is finite. Denote by $g(s|\theta)$ the probability that the planner assigns a score $s \in S$ when he observes type θ; that is, $g(s|\theta) = \Pr(\tilde{s} = s|\tilde{\theta} = \theta)$. (For every $\theta \in \Theta$, $\sum_{s\in S} g(s|\theta) = 1$.) For example, full disclosure is obtained when for every type θ, the planner assigns some score $s_\theta \in S$ with probability 1, such that $s_\theta \neq s_{\theta'}$ if $\theta \neq \theta'$. No disclosure is obtained when the planner assigns the same distribution over scores to all types; e.g., each type obtains the same score.

For use below, denote $\mu(s) = E[\tilde{\theta} + \tilde{\varepsilon}|\tilde{s} = s)]$, which is the expected value of the bank's asset conditional on the bank obtaining score s. Since $\tilde{\varepsilon}$ is independent of $\tilde{\theta}$, and since $E(\tilde{\varepsilon}) = 0$, we obtain that

$$\mu(s) = E[\tilde{\theta}|\tilde{s} = s] = \sum_{\theta\in\Theta} \theta \Pr(\tilde{\theta} = \theta|\tilde{s} = s) = \frac{\sum_{\theta\in\Theta} \theta p(\theta) g(s|\theta)}{\sum_{\theta\in\Theta} p(\theta) g(s|\theta)}, \tag{2}$$

where the last equality follows from Bayes' rule.

2.3 Sequence of events

We assume that the planner can commit to assigning scores according to the disclosure rule chosen. Hence, the sequence of events is as follows:

$t = 0:$ (a) The planner announces its disclosure rule.

(b) The bank's type θ is realized and observed by the planner.

(c) The planner assigns the bank a score s, according to the disclosure rule, and publicly announces the score.

(d) The market offers to purchase the asset at a price $x(s)$.

(e) The bank either keeps the asset or sells it for a price $x(s)$.

$t = 1:$ The bank invests if its available cash z is above 1.

$t = 2:$ The bank obtains $R(z)$.

The planner's disclosure rule and assigned scores specify a game between the bank and the market. We focus on perfect Bayesian equilibria of this game. Specifically, the bank chooses whether to sell or keep the asset to maximize its expected profits, conditional on its information, and the market chooses a price $x(s)$ that equals the expected value of the asset conditional on public information, taking as given the bank's equilibrium strategy. We assume that if the bank is indifferent between selling and not selling, it sells. The planner chooses a disclosure rule that maximizes the bank's expected utility, taking as given the equilibrium strategies of the market and of the bank.

Finally, note that there is a big difference between the bank and the planner even in the second case in which the bank and the planner share the same information about θ. The bank maximizes its ex-post utility after θ is realized. The planner maximizes the bank's ex-ante utility before θ is realized. If there are many banks, one can think of $p(\theta)$ as the fraction of banks with a realization of θ. In this case, maximizing the bank's ex-ante utility is the same as maximizing the sum of banks' ex-post utilities. Hence, the bank and the planner have different objective functions ex post: the bank cares only about its own utility, while the planner cares about the sum of utilities of all banks.

3 Bank does not observe its type

We start with the case in which the bank observes only the score s. We solve the game backward. One observation that simplifies the analysis is that the bank's decision of whether to sell the asset depends on s but not on θ or ε. Hence, the fact that the bank sells the asset does not convey any additional information to the market. Consequently, the market sets a price $x(s) = \mu(s)$, which is the expected value of the bank's asset conditional on the bank obtaining score s. Given that, the bank's decision is as follows:

Lemma 1 *In equilibrium, the bank sells the asset if and only if* $\mu(s) \geq 1$*.*

The proof of Lemma 1 and all other proofs are in the appendix. The idea behind Lemma 1 is simple. If $\mu(s) > 1$, selling guarantees that the bank will have sufficient funds to invest in its positive NPV project; hence, the bank is happy to replace the asset's random cash flow with its expected value. If instead, $\mu(s) < 1$, the bank prefers to keep the asset because if the bank sells the asset, the bank will surely not have sufficient funds to invest, but if the bank keeps the asset, there is a positive probability that the asset's cash flow will turn out to be high and the bank will have sufficient funds. Essentially, due to the payoff structure in (1), the bank acts as a risk-loving agent when the expected payoff is below 1 and as a risk-averse agent when the expected payoff is above 1. This follows from the fact that the bank receives a "bonus" on its assets when the value of the assets is above 1 (or alternatively, the bank receives a "penalty" when the value falls below 1).

The expected utility for a bank of type θ, given that the planner follows a disclosure rule (S, g), is then

$$u(\theta) \equiv \sum_{s:\mu(s)<1} E[R(\theta + \tilde{\varepsilon})]g(s|\theta) + \sum_{s:\mu(s)\geq 1} R(\mu(s))g(s|\theta). \tag{3}$$

The first term represents the cases in which the bank keeps the asset, and the second term represents the cases in which the bank sells the asset.

The planner's problem is to choose a disclosure rule (S, g) to maximize the bank's ex-ante expected utility $\sum_{\theta\in\Theta} p(\theta)u(\theta)$.

Denote the probability that a bank of type θ sells the asset by $h(\theta)$; that is, $h(\theta) = \sum_{s:\mu(s)\geq 1} g(s|\theta)$. As noted earlier, this is the probability that a bank of type θ can engage in a risk-sharing arrangement.

Lemma 2 *The planner's problem reduces to finding a function $h : \Theta \to [0, 1]$ to maximize*

$$\sum_{\theta\in\Theta} p(\theta) \Pr(\tilde{\varepsilon} < 1 - \theta)h(\theta), \tag{4}$$

subject to the constraint

$$\sum_{\theta\in\Theta} p(\theta)(\theta - 1)h(\theta) \geq 0. \tag{5}$$

The objective function (4) represents the benefits from risk sharing. The planner maximizes the probability that banks with a low realization of cash flow will be able to sell their assets and guarantee that they have the necessary amount to invest and receive the net present value r.

Constraint (5) captures the idea that risk sharing is possible only if there are sufficient resources. Formally, for every score s that induces the bank to sell its asset, we must have $\mu(s) \geq 1$ (Lemma 1). It then follows from equation (2) that for every such score, we must have $\sum_{\theta\in\Theta} p(\theta)(\theta - 1)g(s|\theta) \geq 0$. Summing over all scores with $\mu(s) \geq 1$, we obtain constraint (5).

One can think of constraint (5) as the planner's resource constraint. The planner would like to implement an outcome in which every bank engages in risk sharing. However, the planner faces a constraint that the average cash flow of banks that participate in risk sharing must be at least 1. Essentially, the planner implements a transfer of resources from types with $\theta > 1$ to types with $\theta < 1$, so a high type sells its asset for less than what the asset is truly worth, and a low type sells its asset for more than what the asset is worth.

Effectively, the only effect of the disclosure rule is to determine whether a bank is going to sell the asset or not. Since we know that banks sell when $\mu(s) \geq 1$ and do not sell otherwise, we can focus on a disclosure rule that assigns at most two scores: a "low" score s_0 such that $\mu(s_0) < 1$ and a "high" score s_1 such that $\mu(s_1) \geq 1$. Types that obtain a high score sell the asset, and types that obtain a low score keep the asset. In this case, $h(\theta)$ is the probability that type θ obtains the high score.

Proposition 1 below characterizes the optimal disclosure rule. The derivation of the result is as follows (the proof contains more details):

When $\theta \geq 1$, increasing $h(\theta)$ increases the objective function and relaxes the constraint; hence, the optimal disclosure rule is such that $h(\theta) = 1$ for every $\theta \geq 1$. In contrast, when $\theta < 1$, increasing $h(\theta)$ increases the objective function but *tightens* the constraint. If $E(\tilde{\theta}) \geq 1$, assigning $h(\theta) = 1$ for every $\theta \in \Theta$ satisfies the constraint and hence is optimal. Otherwise, the resource constraint is binding, and the optimal disclosure rule depends on the "gain-to-cost ratio"

$$G(\theta) \equiv \frac{\Pr(\tilde{\varepsilon} < 1 - \theta)}{1 - \theta}. \tag{6}$$

The numerator reflects the gain from increasing $h(\theta)$, and the denominator reflects the cost. The gain is that type θ can invest in its project even if it has a low realization of cash flow. The cost is that type θ requires resources in the amount $1 - \theta$.

Since the problem is linear, it is optimal to assign $h(\theta) = 1$ to types with high gain-to-cost ratios and $h(\theta) = 0$ to types with low ratios. In other words, types with high gain-to-cost ratios obtain the high score, s_1, and types with low gain-to-cost ratios obtain the low score, s_0. Since there is a finite number of types, there could also be a type that obtains the high score with a probability $h(\theta) \in (0, 1)$. To simplify the exposition, we focus on the case in which $G(\theta_1) \neq G(\theta_2)$ if $\theta_1 \neq \theta_2$, so there is at most one such type. The probability that this type obtains the high score is such that the resource constraint is satisfied with equality.

For use below, we order the types in $\{\theta \in \Theta : \theta < 1\}$ according to their gain-to-cost ratios $G(\theta)$, such that b_1 is the type with the highest ratio, b_2 is the type with the second highest ratio, and so on. Also, let l^* be the largest integer i, such that $E(\theta|\theta \geq 1 \cup \theta \in \{b_1, ..., b_i\}) \geq 1$. Then the type that could have $h(\theta) \in (0, 1)$ is type b_{l^*+1}.

Proposition 1 *Assume that the bank does not observe its type.*

(i) If $E(\tilde{\theta}) \geq 1$, the optimal disclosure rule is such that $h(\theta) = 1$ for every $\theta \in \theta$.

(ii) If $E(\tilde{\theta}) < 1$, the optimal disclosure rule is such that

$$h(\theta) = \begin{cases} 1 \text{ if } \theta \geq 1 \text{ or } \theta \in \{b_1, ..., b_{l^*}\} \\ 0 \text{ if } \theta < 1 \text{ and } \theta \notin \{b_1, ..., b_{l^*}, b_{l^*+1}\}. \end{cases} \tag{7}$$

(For type b_{l^*+1}, $h(b_{l^*+1})$ is found from the resource constraint: $h(b_{l^*+1})p(b_{l^*+1})(1 - b_{l^*+1}) = \sum_{\theta \geq 1 \text{ or } \theta \in \{b_1,...,b_{l^*}\}} p(\theta)(\theta - 1)$.)

The first part in Proposition 1 says that if there are sufficient resources, every bank must obtain a score that induces selling; that is, every bank obtains a score, such that $\mu(s) \geq 1$. This can be implemented by giving all banks the same score; i.e., no disclosure. This can also be implemented by assigning more than one score such that the average cash flows of a bank receiving each score is at least 1. In particular, in the special case $\theta_{\min} \geq 1$, the optimal disclosure rule can be implemented by assigning a different score to each type; i.e., full disclosure.

The second part says that if there are insufficient resources, the planner must assign at least two scores, a high score, s_1, and a low score, s_0. The high score pools all the types that are at or above 1 with some type that are below 1, such that the average cash flows of banks receiving the high score equals 1. In this case, full disclosure is suboptimal because under full disclosure, only types above 1 sell their assets, whereas under the optimal disclosure rule, some types that are below 1 also sell their assets.

Corollary 1 *Assume that the bank does not observe its type:*

1. *Full disclosure is optimal if and only if* $\theta_{\min} \geq 1$*.*
2. *No disclosure is optimal if and only if* $E(\tilde{\theta}) \geq 1$*.*

In general, the banks that obtain the low score in the second part of Proposition 1 are not necessarily the lowest types. In other words, the banks that are shunned from risk-sharing arrangements are not necessarily the lowest types. However, if the gains-to-cost function $G(\theta)$ is increasing when $\theta < 1$, then types that obtain low scores are the low types. In this case, the optimal disclosure rule involves a cutoff, such that types above the cutoff obtain a high score and types below the cutoff obtain a low score. A sufficient condition for this to happen is that the probability distribution of the idiosyncratic risk satisfies the following condition:

Condition 1 $F(\varepsilon)/\varepsilon$ *is decreasing when* $\varepsilon > 0$*.*

Corollary 2 *If* $E(\tilde{\theta}) < 1$*, and if Condition (1) is satisfied, the optimal disclosure rule involves a cutoff such that types below the cutoff obtain a low score (and hence do not engage in risk sharing) and types above the cutoff obtain a high score (and hence engage in risk sharing).*

Any probability distribution function that is concave on the positive region satisfies Condition (1). Examples are a normal distribution with mean zero and a uniform distribution. Also note that condition (1) is equivalent to saying that $\frac{F(\varepsilon)}{\varepsilon} > F'(\varepsilon)$ for every $\varepsilon > 0$.

Finally, we assumed above that all types of banks have the same r, that is, the same investment opportunities. The results extend easily to the case in which r depends on the bank's type according to some function $r(\theta)$. In this case, the gain-to-cost ratio becomes $r(\theta)G(\theta)$. Everything else being equal, the gain of giving a high score is higher if the bank's continuation value is higher. Hence, if $r'(\theta) > 0$, the optimal rule may involve a cutoff even if Condition (1) does not hold.

4 Bank observes its type

So far, we assumed that the bank does not observe its type. We showed that it is possible to implement the optimal disclosure rule with two scores, such that the planner pools everyone who sells under the same score. In this section, we show that this conclusion may no longer be true when the bank observes its type. The difference is that now each type has a "reservation price," i.e., a minimum price at which it is willing to sell. When different types have different reservation prices, the planner may need to assign more than two scores to distinguish among them. We also discuss how the planner should assign these multiple scores to low types who are pooled with high types.

We first derive banks' reservation prices. Define

$$\rho(\theta) = \begin{cases} \max\{1, \theta - r\Pr(\tilde{\varepsilon} < 1 - \theta)\} \text{ if } \theta \geq 1 \\ \min\{1, \theta + r\Pr(\tilde{\varepsilon} \geq 1 - \theta)\} \text{ if } \theta < 1. \end{cases} \tag{8}$$

Then,

Lemma 3 *A bank of type θ will sell its asset if and only if the price is at least $\rho(\theta)$.*

We refer to $\rho(\theta)$ as type θ's reservation price. As illustrated in Figure 1, the reservation price is increasing in θ. For high types, $\theta > 1$, the reservation price is lower than the true value θ because these types are willing to pay a premium $r\Pr(\tilde{\varepsilon} < 1 - \theta)$ to guarantee that they will have the minimum amount necessary for investment. But the price must be at least one for this type of insurance to work. Low types, $\theta < 1$, should also have at least one dollar if they want to insure themselves, but the very low types may be willing to sell their assets for even less than one dollar. Such a sale goes against insurance, so the very low types will be willing to do so only if the price is strictly higher than the true value.

If $\rho(\theta_{\max}) = 1$, so the highest reservation price is one, the optimal disclosure rule from Section 3 remains optimal. The case $\rho(\theta_{\max}) = 1$ happens when $\theta_{\max} - r\Pr(\tilde{\varepsilon} <$

$1-\theta_{\max}) \leq 1$; i.e., when r is sufficiently high, so the cost of not obtaining insurance is very high, or when $\theta_{\max}$ is sufficiently low, so the cost of selling at a price of 1 rather than the true value $\theta_{\max}$ is not too high.

Proposition 2 *If $\theta_{\max} - r \Pr(\tilde{\varepsilon} < 1 - \theta_{\max}) \leq 1$, i.e., r is sufficiently high or $\theta_{\max}$ is sufficiently low, Proposition 1 continues to hold even if banks observe their types.*

The rest of this section focuses on the more interesting case $\rho(\theta_{\max}) > 1$. We first establish that:

Lemma 4 *Under an optimal disclosure rule:*

1. *Every type $\theta \geq 1$ sells its asset with probability 1.*
2. *Whenever type $\theta \geq 1$ receives score s, the price is $x(s) = \mu(s)$.*
3. *If the highest type that obtains score s is less than 1, then every type keeps its asset upon obtaining score s.*

The idea behind the first part in Lemma 4 is that if a type $\theta \geq 1$ did not sell its asset, the planner could strictly increase the utility of that type, without affecting the utilities of other types, by fully revealing θ's type. Then the market would offer to buy the asset of type θ at a price θ, and type θ would accept the offer.

The second part in Lemma 4 follows from the first part and the observation that the reservation price is increasing in θ. These imply that every type sells its asset upon obtaining score s, and hence selling does not convey any additional information to the market.

The third part in Lemma 4 reflects the fact that if there is no type above 1 that obtains score s, the price $x(s)$ must be less than 1. But then banks will sell only if the price is strictly above their true value. However, this cannot be an equilibrium outcome, since the market would lose money. Note that this result holds under any disclosure rule, not only an optimal one.

For use below, denote the types in Θ by $\theta_{\max} = \theta_1 > \theta_2 > ... > \theta_m = \theta_{\min}$ and suppose that $\theta_k \geq 1 > \theta_{k+1}$, so there are exactly k types at or above 1. Denote $\rho_i = \rho(\theta_i)$.

Denote by S_i the set of scores that type θ_i obtains with a positive probability but higher types do not obtain; that is, $S_i = \{s \in S : g(s|\theta_i) > 0$ and $g(s|\theta') = 0$ for every $\theta' > \theta\}$. From Lemma 3 and Lemma 4, we know that for each $i \in \{1, ..., k\}$ and $s \in S_i$, we must have

$$x(s) = \mu(s) \geq \rho_i. \tag{9}$$

That is, if the highest type that obtains score s is type $\theta_i \geq 1$, the expected cash flow conditional on obtaining score s must be at least as high as type θ_i's reservation price. From equation (2), equation (9) reduces to

$$\sum_{\theta \in \Theta} p(\theta)(\theta - \rho_i) g(s|\theta) \geq 0. \tag{10}$$

Equation (10) is a generalization of the resource constraint (5).

As in Corollary 1, full disclosure is optimal only if there are no types below 1. No disclosure is optimal only if there are sufficient resources, but the condition for no disclosure changes to $E(\tilde{\theta}) \geq \rho_1$, so that equation (9) holds for the highest type.

The rest of this section focuses on the case in which resources are scarce, so the optimal disclosure rule is such that there is at least one type that keeps its asset with a positive probability. A sufficient condition for this to happen is that $E(\tilde{\theta}) < 1$. In this case, all resource constraints are binding. In particular, if the highest type that obtains score s is $\theta_i \geq 1$, the price must equal ρ_i. This means that all lower types that obtain score s also sell for a price ρ_i. An implication of this is that if types $\theta_i > \theta_j \geq 1$ have different reservation prices (which is the case when $\rho_i > 1$), the planner must assign them different scores. Formally,

Proposition 3 *Suppose $E(\tilde{\theta}) < 1$. Under an optimal disclosure rule, types that are above 1 and that have different reservation prices must obtain different scores.*

Intuitively, if types $\theta_i > \theta_j \geq 1$ have different reservation prices but the same score, the sale price depends on the reservation price of the highest type. This means that the lowest type sells the asset for more than its reservation price and, therefore, ends up with more resources than it requires. But this is a waste of resources without any gain. The planner can do better by assigning the lower type its own score, so that this type ends up with less resources. This frees up resources that can be used to subsidize types with $\theta < 1$. This, in turn, increases the probability that these low types invest in their projects.

It follows that when $E(\tilde{\theta}) < 1$, and $\rho_1 > \rho_2 > ... > \rho_k$, the planner must assign at least $k+1$ scores, $s_0, s_1, ..., s_k$, such that for each $i \in \{1, ., , , .k\}$, score s_i pools together type θ_i with a type (or types) that are below 1, and score s_0 pools together only types that are below 1. A bank sells its asset if and only if $s \neq s_0$. When a bank obtains score $s_i \neq s_0$, the bank sells the asset at a price ρ_i. Since $\rho_1 > \rho_2 > ... > \rho_k$, it is natural to think of score s_1 as the highest, score s_2 as the second highest, etc. We can assume, without loss of generality, that scores $s_0, s_1, ..., s_k$ are the only scores.[5]

Next we discuss how the planner should assign scores to types that are below 1; that is, how the planner should pool types that are below 1 with types that are above 1. Suppose first that there is only one type above 1, type θ_1. The analysis is similar to the the one in Section 3, but now the gains-to-cost ratio depends on ρ_1:

$$G_1(\theta) \equiv \frac{\Pr(\tilde{\varepsilon} < 1 - \theta)}{\rho_1 - \theta}. \tag{11}$$

In particular, the gain of pooling type $\theta < 1$ with type $\theta_1 > 1$ is the same as in Section 3, but the cost is higher, since type θ ends up with $\rho_1 > 1$ rather that 1. This reflects the fact that when a low type is pooled with a high type, the market price reflects the reservation price of the highest type.

Suppose now that there are two types that are above 1, $\theta_1 > \theta_2 > 1$. The gain from pooling type $\theta < 1$ with either type θ_1 or type θ_2 is the same. However, the

[5] Lemma A-2 in the appendix provides more details.

cost is different: it is less costly to pool type θ with type θ_2 because then type θ ends up with less resources. The "net" benefit of pooling type θ with type θ_2 rather than with type θ_1 is

$$\frac{G_2(\theta)}{G_1(\theta)} = \frac{\Pr(\tilde{\varepsilon} < 1-\theta)}{\rho_2 - \theta} \frac{\rho_1 - \theta}{\Pr(\tilde{\varepsilon} < 1-\theta)} = \frac{\rho_1 - \theta}{\rho_2 - \theta} > 1. \tag{12}$$

Since the net benefit is higher when θ is higher, the planner would prefer to pool type θ_2 with higher types (among those with $\theta < 1$) and type θ_1 with lower types. Hence, if, for example, $\theta' < \theta'' < 1$, we may obtain an outcome in which type θ' is pooled with type θ_1 and sells its asset for price ρ_1, and type θ'' is pooled with type θ_2 and sells it asset for a price ρ_2. In this case, the lower types sells for a higher price; that is, the lower type obtains a higher score.

The intuition above extends to the case in which there are more than two types above 1. Formally,

Proposition 4 *Suppose $E(\tilde{\theta}) < 1$ and $\theta' < \theta'' < 1$. Under an optimal disclosure rule, if there is a positive probability that type θ' obtains score $s' \neq s_0$ and type θ'' obtains score $s'' \neq s_0$, then the prices must satisfy $x(s'') \leq x(s')$. In other words, among the types $\theta < 1$ that sell their assets, lower types obtain higher scores.*

Propositions 3 and 4 imply that when banks observe their types, the sale price is increasing in type when $\theta > 1$ but decreasing in type when $\theta < 1$. Hence, non-monotonicity is a general feature of optimal disclosure rules. (In contrast, in Section 3, all types that sell their assets sell for the same price, and only the probability of selling the asset could be non-monotone.) The next example illustrates this.

Example 1 Suppose that there are eight types: $\theta_1 > \theta_2 > 1 > \theta_3 > ... > \theta_8$. Suppose that $\rho_1 > \rho_2 \geq 1$ and $E(\tilde{\theta}) < 1$. Then we need at least three scores: s_0, s_1, and s_2. Suppose the gains-to-cost functions that are associated with score s_1 and score s_2 are both increasing in θ; that is, the functions $G_1(\theta) = \frac{\Pr(\tilde{\varepsilon}<1-\theta)}{\rho_1-\theta}$ and

$G_2(\theta) = \frac{\Pr(\tilde{\varepsilon}<1-\theta)}{\rho_2-\theta}$ are both increasing in θ (see Figure 2). Suppose

$$p_2(\theta_2 - \rho_2) = p_3(\rho_2 - \theta_3) + \frac{1}{3}p_4(\rho_2 - \theta_4) \tag{13}$$

$$p_1(\theta_1 - \rho_1) = \frac{2}{3}p_4(\rho_1 - \theta_4) + \frac{1}{5}p_5(\rho_1 - \theta_5) \tag{14}$$

As will become clear, equation (13) is the resource constraint that is associated with score s_2, and equation (14) is the resource constraint that is associated with score s_1.

The optimal disclosure rule is as follows. (Each element in the table is the probability of assigning score s to type θ.)

	θ_8	θ_7	θ_6	θ_5	θ_4	θ_3	θ_2	θ_1
s_1				$\frac{1}{5}$	$\frac{2}{3}$			1
s_2					$\frac{1}{3}$	1	1	
s_0	1	1	1	$\frac{4}{5}$				

To see why, note that since $G_1(\theta)$ and $G_2(\theta)$ are both increasing in θ, score s_0 is given to low types. (Note that since $\rho_1 > \rho_2$, $G_1(\theta)$ is below $G_2(\theta)$ for every $\theta < 1$.) Regarding scores s_1 and s_2, we know from Proposition 3 that with probability 1, type θ_1 obtains score s_1, and type θ_2 obtains score s_2. As for the other types, which are below 1, we know from Proposition 4 that score s_2 is given to higher types compared with score s_1. It then follows from equation (13) that score s_2 is first given to type θ_3. Since there are remaining resource even if type θ_3 obtains score θ_3 with probability 1, score s_2 is also given to type θ_4, but only with probability $\frac{1}{3}$. This exhausts all resources that type θ_2 contributes. Similarly, score s_1 is given to the next highest types until all resources are exhausted. Hence, type θ_4 obtains score s_1 with probability $\frac{2}{3}$ (so that it sells its asset with probability 1), and type θ_5 obtains score s_1 with probability $\frac{1}{5}$, so that the resource constraint (14) is satisfied with equality. All remaining types obtain score s_0. ■

Note that while the sale price in Example 1 is non-monotone in type, the probability of selling the asset is monotone. In particular, as in Corollary 2, there exists a cutoff such that types above the cutoff sell their asset, and types below the cutoff do not sell. This follows since we assumed in the example that the gains-to-cost function that is associated with each score $s \neq s_0$ is increasing in θ. A sufficient condition for this to happen is that condition 1 holds and ρ_1 is sufficiently low.[6] However, if ρ_1 is sufficiently high, condition 1 implies that the gains-to-cost function $G_1(\theta)$ is decreasing in θ.[7] In this case, there does not exist a cutoff such that types above the cutoff sell and types below the cutoff do not sell. Hence, we obtain two forms of non-monotonicity: First, the probability of selling the price does not increase in type. Second, the sale price does not increase in type. The next example illustrates this.

Example 2 Consider Example 1 but assume that ρ_1 is sufficiently high, so that $G_1(\theta)$ is decreasing in θ. In addition, instead of equation (14), assume that

$$p_1(\theta_1 - \rho_1) = p_8(\rho_1 - \theta_8) + \frac{1}{10} p_7(\rho_1 - \theta_7), \tag{15}$$

which will be the resource constraint that is associated with score s_1. In this case, the optimal disclosure rule is

	θ_8	θ_7	θ_6	θ_5	θ_4	θ_3	θ_2	θ_1
s_1	1	$\frac{1}{10}$						1
s_2					$\frac{1}{3}$	1	1	
s_0		$\frac{9}{10}$	1	1	$\frac{2}{3}$			

In particular, as before, score θ_2 is assigned to type θ_3 and type θ_4, such that the resource constraint (13) is binding. However, since the gains-to-cost function that is associated with score s_1 is decreasing in type, score s_1 is given to the lowest type. Hence, type θ_8 obtains score s_1 with probability 1, and type θ_7 obtains score s_1 with probability $\frac{1}{10}$. Then the resource constraint (15) is satisfied with equality. The remaining score s_0, is given to all remaining types (those in the middle). Hence, the probability of selling the asset $(1 - s_0)$ is non-monotone. ■

[6] To see that, note that $G_i(\theta)$ increases when $\theta < 1$ if and only if $F(\varepsilon)/(\varepsilon + \rho_i - 1)$ is decreasing when $\varepsilon > 0$, or equivalently, if for every $\varepsilon > 0$, $\frac{F(\varepsilon)}{F'(\varepsilon)} > \varepsilon + \rho_i - 1$. By continuity, if ρ_i is sufficiently small ($\rho_i \downarrow 1$), condition 1 implies $\frac{F(\varepsilon)}{F'(\varepsilon)} > \varepsilon + \rho_i - 1$.

[7] In particular, $\frac{F(\varepsilon)}{F'(\varepsilon)} < \varepsilon + \rho_i - 1$ for every $\varepsilon > 0$, so $G_1(\theta)$ is decreasing when $\theta < 1$.

5 Conclusion

Our paper provides a model of an optimal disclosure policy of a regulator, who has information about banks (e.g., the regulator has conducted stress tests). The regulator's disclosure policy affects whether banks can take corrective actions, particularly whether banks can engage in risk-sharing arrangements to protect themselves against the possibility that their future capital falls below some critical level. We show that during normal times, no disclosure is necessary, but during bad times, partial disclosure is needed. Partial disclosure takes the form of different scores pooling together banks of different levels of strength. Two scores are sufficient if banks do not have the information that the regulator has. In this case, the optimal disclosure rule may take a simple form, such that banks whose forecasted capital is below some threshold obtain the low score and banks whose forecasted capital is above the threshold obtain the high score; we provide conditions for this to happen. More than two scores may be needed if a bank shares the same information that the regulator has about the bank. In this case, the optimal disclosure rule is non-monotone: among the strong banks, the stronger banks obtain higher scores, but among the weak banks that are pooled with strong banks, the weaker banks obtain higher scores.

References

[1] Admati, Anat, and Paul Pfleiderer (2000). Forcing Firms to Talk: Disclosure Regulation and Externalities, *Review of Financial Studies*, 13, 479-519.

[2] Allen, Franklin, and Douglas Gale (2000). Financial Contagion, *Journal of Political Economy*, 108, 1-33.

[3] Angeletos, George-Marios, and Alessandro Pavan (2007). Efficient Use of Information and Social Value of Information, *Econometrica*, 75, 1103-1142.

[4] Bond, Philip, and Itay Goldstein (2012). Government Intervention and Information Aggregation by Prices, Working paper.

[5] Burkart, Mike, Denis Gromb, and Fausto Panunzi (1997). Large Shareholders, Monitoring, and the Value of Firms. *Quarterly Journal of Economics*, 112, 693-728.

[6] Diamond, Douglas (1985). Optimal Release of Information by Firms, *Journal of Finance*, 60, 1071-1094.

[7] Fishman, Michael, and Kathleen Hagerty (1990). The Optimal Amount of Discretion to Allow in Disclosure, *Quarterly Journal of Economics*, 427-444.

[8] Fishman, Michael, and Kathleen Hagerty (2003). Mandatory Versus Voluntary Disclosure in Markets with Informed and Uninformed Customers, *Journal of Law, Economics, and Organization*, 19, 45-63.

[9] Goldstein, Itay, and Haresh Sapra (2012). Should Banks' Stress Test Results be Disclosed? An Analysis of the Costs and Benefits, working paper.

[10] Grossman, Sanford (1981). The Informational Role of Warranties and Private Disclosure About Product Quality, *Journal of Law and Economics*, 24, 461-483.

[11] Hirshleifer, Jack (1971). The Private and Social Value of Information and the Reward to Inventive Activity, *American Economic Review*, 61, 561-574.

[12] Kamenica, Emir, and Matthew Gentzkow (2011). Bayesian Persuasion, *American Economic Review*, 101, 2590-2615.

[13] Kartasheva, Anastasia, and Bilge Yilmaz (2012). Precision of Ratings, manuscript.

[14] Leitner, Yaron (2005). Financial Networks: Contagion, Commitment, and Private Sector Bailouts, *Journal of Finance*, 60, 2925-2953.

[15] Leitner, Yaron (2012). Inducing Agents to Report Hidden Trades: A Theory of an Intermediary, *Review of Finance*, 16, 1013-1042.

[16] Lizzeri, Alessandro (1999). Information Revelation and Certification Intermediaries, *Rand Journal of Economics*, 30, 214-231.

[17] Marin, Jose M., and Rohit Rahi (2000). Limited Information Revelation and Market Incompleteness, *Review of Economic Studies*, 67, 455-481.

[18] Morris, Stephen, and Hyun Song Shin (2002). Social Value of Public Information, *American Economic Review*, 92, 1521-1534.

[19] Prescott, Edward Simpson (2008). Should Bank Supervisors Disclose Information About Their Banks? Federal Reserve Bank of Richmond *Economic Review,* 94, 1-16.

Appendix

Proof of Lemma 1. From the text, the equilibrium price is $x(s) = \mu(s)$. If the bank sells the asset at price $\mu(s)$, its final payoff is $R(\mu(s))$. If the bank keeps the asset, its (expected) final payoff, conditional on its information, is $E[R(\tilde{\theta} + \tilde{\varepsilon}|\tilde{s} = s)] = \mu(s) + r\Pr(\tilde{\theta} + \tilde{\varepsilon} \geq 1|\tilde{s} = s)$. Hence, if $\mu(s) \geq 1$, it is optimal to sell, since $R(\mu(s)) = \mu(s) + r > E[R(\tilde{\theta} + \tilde{\varepsilon}|\tilde{s} = s)]$. If $\mu(s) < 1$, it is optimal to keep the asset, since $R(\mu(s)) = \mu(s) < E[R(\tilde{\theta} + \tilde{\varepsilon}|\tilde{s} = s)]$. The strict inequality follows from Assumption 1. Q.E.D.

Proof of Lemma 2. The planner's problem is to find a disclosure rule (S, g) to maximize $\sum_{\theta \in \Theta} p(\theta)u(\theta)$. Since equation (3) reduces to

$$u(\theta) = \sum_{s:\mu(s)<1} [\theta + r\Pr(\tilde{\varepsilon} \geq 1 - \theta)]g(s|\theta) + \sum_{s:\mu(s)\geq 1} [\mu(s) + r]g(s|\theta),$$

it follows that:

$$\begin{aligned}\sum_{\theta\in\Theta} p(\theta)u(\theta) &= \sum_{\theta\in\Theta} p(\theta) \sum_{s:\mu(s)<1} \theta g(s|\theta) + \sum_{\theta\in\Theta} p(\theta) \sum_{s:\mu(s)<1} r\Pr(\tilde{\varepsilon} \geq 1-\theta)g(s|\theta) \\ &\quad + \sum_{\theta\in\Theta} p(\theta) \sum_{s:\mu(s)\geq 1} \mu(s)g(s|\theta) + \sum_{\theta\in\Theta} p(\theta) \sum_{s:\mu(s)\geq 1} rg(s|\theta).\end{aligned}$$

The sum of the first and third terms in the right-hand-side of the equation above reduces to $E(\tilde{\theta})$, as follows:

$$\begin{aligned}&\sum_{\theta\in\Theta} p(\theta) \sum_{s:\mu(s)<1} \theta g(s|\theta) + \sum_{\theta\in\Theta} p(\theta) \sum_{s:\mu(s)\geq 1} \mu(s)g(s|\theta) \\ =& \sum_{\theta\in\Theta} \theta p(\theta) \sum_{s:\mu(s)<1} g(s|\theta) + \sum_{s:\mu(s)\geq 1} \mu(s) \sum_{\theta\in\Theta} p(\theta)g(s|\theta) \\ =& \sum_{\theta\in\Theta} \theta p(\theta) \sum_{s:\mu(s)<1} g(s|\theta) + \sum_{s:\mu(s)\geq 1} \sum_{\theta\in\Theta} \theta p(\theta)g(s|\theta) \\ =& \sum_{\theta\in\Theta} \theta p(\theta) \sum_{s:\mu(s)<1} g(s|\theta) + \sum_{\theta\in\Theta} \theta p(\theta) \sum_{s:\mu(s)\geq 1} g(s|\theta) = E(\tilde{\theta}),\end{aligned}$$

where the third line follows from equation (2). Hence,

$$\begin{aligned}\sum_{\theta\in\Theta} p(\theta)u(\theta) &= E(\tilde{\theta}) + \sum_{\theta\in\Theta} p(\theta) r \Pr(\tilde{\varepsilon} \geq 1-\theta) \sum_{s:\mu(s)<1} g(s|\theta) + r\sum_{\theta\in\Theta} p(\theta) \sum_{s:\mu(s)\geq 1} g(s|\theta) \\ &= E(\tilde{\theta}) + \sum_{\theta\in\Theta} p(\theta) r \Pr(\tilde{\varepsilon} \geq 1-\theta)[1-h(\theta)] + r\sum_{\theta\in\Theta} p(\theta)h(\theta) \\ &= E(\tilde{\theta}) + \sum_{\theta\in\Theta} p(\theta) r \Pr(\tilde{\varepsilon} \geq 1-\theta) + r\sum_{\theta\in\Theta} p(\theta)[1-\Pr(\tilde{\varepsilon} \geq 1-\theta)]h(\theta)\end{aligned}$$

Hence,

$$\sum_{\theta\in\Theta} p(\theta)u(\theta) = E(\tilde{\theta}) + r\sum_{\theta\in\Theta} p(\theta)\Pr(\tilde{\varepsilon} \geq 1-\theta) + r\sum_{\theta\in\Theta} p(\theta)\Pr(\tilde{\varepsilon} < 1-\theta)h(\theta) \quad \text{(A-1)}$$

The first two terms in the right-hand side of (A-1) are exogenous and are not affected by the planner's disclosure rule. Only the third term is endogenous and affected by the planner's disclosure rule. Hence, maximizing $\sum_{\theta\in\Theta} p(\theta)u(\theta)$ is equivalent to maximizing (4).

From Lemma A-1 below, we can focus, without loss of generality, on disclosure rules with only two scores, s_0, and s_1, such that $\mu(s_0) < 1$ and $\mu(s_1) \geq 1$. From Lemma 1, we know that $h(\theta) = g(s_1|\theta)$. Hence, the relevant constraint is $\mu(s_1) \geq 1$. From equation (2), the constraint $\mu(s_1) \geq 1$ reduces to $\sum_{\theta\in\Theta} p(\theta)(\theta-1)g(s_1|\theta) \geq 0$, which is equivalent to constraint (5). Q.E.D.

Lemma A-1 *Assume that the bank does not observe its type. For every disclosure rule (S, g), we can construct a disclosure rule that induces the same probability that a bank of type θ sells its asset (i.e., $h(\theta)$) but that uses only two scores, s_0, s_1, such that $\mu(s_0) < 1$ and $\mu(s_1) \geq 1$.*

Proof of Lemma A-1. For a given disclosure rule (S, g), define a disclosure rule $(\tilde{S}, \tilde{g})$, such that $\tilde{S} = \{s_0, s_1\}$ and such that for every $\theta \in \Theta$, $\tilde{g}(s_0|\theta) = \sum_{s:\mu(s)<1} g(s|\theta)$ and $\tilde{g}(s|\theta) = \sum_{s:\mu(s)\geq 1} g(s|\theta)$. From Lemma 1, we need to show that $\mu_{\tilde{g}}(s_1) \geq 1$ and $\mu_{\tilde{g}}(s_0) < 0$, where the subscript $\tilde{g}$ indicates that the expected values are given disclosure rule $(\tilde{S}, \tilde{g})$. To see why $\mu_{\tilde{g}}(s_1) \geq 1$, observe that:

$$\begin{aligned}
\mu_{\tilde{g}}(s_1) &= \frac{\sum_{\theta\in\Theta} \theta p(\theta)\tilde{g}(s_1|\theta)}{\sum_{\theta\in\Theta} p(\theta)\tilde{g}(s_1|\theta)} = \frac{\sum_{\theta\in\Theta} \theta p(\theta) \sum_{s:\mu(s)\geq 1} g(s|\theta)}{\sum_{\theta\in\Theta} p(\theta) \sum_{s:\mu(s)\geq 1} g(s|\theta)} \\
&= \frac{\sum_{s:\mu(s)\geq 1} \sum_{\theta\in\Theta} \theta p(\theta) g(s|\theta)}{\sum_{s:\mu(s)\geq 1} \sum_{\theta\in\Theta} p(\theta) g(s|\theta)} = \frac{\sum_{s:\mu(s)\geq 1} \mu(s) \sum_{\theta\in\Theta} p(\theta) g(s|\theta)}{\sum_{s:\mu(s)\geq 1} \sum_{\theta\in\Theta} p(\theta) g(s|\theta)} \\
&\geq \frac{\sum_{s:\mu(s)\geq 1} \sum_{\theta\in\Theta} p(\theta) g(s|\theta)}{\sum_{s:\mu(s)\geq 1} \sum_{\theta\in\Theta} p(\theta) g(s|\theta)} = 1,
\end{aligned}$$

where the first and fourth equalities follow from equation (2) and the second equality follows from the definition of $\tilde{g}$. Similarly, we can show that $\mu_{\tilde{g}}(s_0) < 1$. Q.E.D.

Proof of Proposition 1.

Part (A): Assigning $h(\theta) = 1$ for every $\theta \in \theta$ achieves the maximal attainable value for the objective function and satisfies the planner's resource constraints. Any other disclosure rule reduces the value of the objective function, by Assumption 1.

Part (B): First, by Assumption 1, it is clearly (uniquely) optimal to set $h(\theta) = 1$ for every $\theta \geq 1$. In addition, if $h(b_j) > 0$ for some j, it is optimal to set $h(b_i) = 1$ for every $i < j$. To see why, suppose, by contradiction, that under an optimal disclosure rule there exists $i < j$, such that $h(b_j) > 0$ but $h(b_i) < 1$. Consider a small $\Delta > 0$, let $\Delta' = \frac{P(b_i)}{P(b_j)} \frac{1-b_i}{1-b_j} \Delta$, and consider an alternate disclosure rule in which we increase $h(b_i)$ by Δ and reduce $h(b_j)$ by Δ'. We obtain a contradiction to the optimality of the original by showing that the alternate rule increases the value of the objective function without violating the resource constraint. In particular, since type b_i has a higher gains-to-cost ratio than type b_j, it follows that $\Delta P(b_i) \Pr(\tilde{\varepsilon} < 1 - b_i) > \Delta \frac{P(b_i)}{P(b_j)} \frac{1-b_i}{1-b_j} P(b_j) \Pr(\tilde{\varepsilon} < 1 - b_j)$, and so the alternate rule increases the value of the objective function. In addition, since $\Delta P(b_i)(b_i - 1) = \Delta \frac{P(b_i)}{P(b_j)} \frac{1-b_i}{1-b_j} P(b_j)(b_j - 1)$, the resource constraint remains unchanged.

Since $\theta_{\max} > 1$, the resource constraint is slack if $h(\theta) = 0$ for every $\theta < 1$. Hence, under the optimal disclosure rule, there exists i, such that $h(b_j) > 0$. Denote the lowest such j by j^*. Then $h(b_i) = 0$ when $i > j^*$, and it follows from above that $h(b_i) = 1$ when $i < j^*$. Finally, note that if $j^* \neq l^*$, it is possible to increase the objective function without violating the constraint. Q.E.D.

Proof of Corollary 1.

Part 1: Under full disclosure, type θ is offered a price θ, and hence, type θ sells its asset if and only if $\theta \geq 1$ (Lemma 1). Hence, under full disclosure, $h(\theta) = 1$ if and only if $\theta \geq 1$. If $\theta_{\min} \geq 1$, then $E(\tilde{\theta}) \geq 1$ and full disclosure is optimal by the first part of Proposition 1. If $\theta_{\min} < 1$, then either $E(\tilde{\theta}) \geq 1$, and full disclosure is suboptimal by the first part of Proposition 1, or else $E(\tilde{\theta}) < 1$ and full disclosure is suboptimal by the second part of Proposition 1. In particular, under full disclosure, $h(\theta) = 0$, for every $\theta < 1$, while under the optimal disclosure rule, there must exist $\theta' > 0$, such that $h(\theta') > 0$. The last statement follows since $\theta_{\max} > 1$.

Part 2: Under no disclosure, every bank is offered a price $E(\tilde{\theta})$. Hence, it follows from Lemma 1 that under no disclosure, the bank will sell its asset if and only if $E(\tilde{\theta}) \geq 1$. Hence, if $E(\tilde{\theta}) \geq 1$, we know from the first part of Proposition 1 that no disclosure is optimal. If $E(\tilde{\theta}) < 1$, we know from the second part of Proposition 1 that no disclosure is suboptimal because under the optimal disclosure rule, at least some banks sell (since $\theta_{\max} > 1$.) Q.E.D.

Proof of Corollary 2. From Proposition 1, it is sufficient to show that if condition 1 holds, $G(\theta) = \frac{F(1-\theta)}{1-\theta}$ is increasing in θ whenever $\theta < 1$. Denote $\varepsilon = 1 - \theta$. Then we need to show that $\frac{F(\varepsilon)}{\varepsilon}$ is decreasing in ε whenever $\varepsilon > 0$. This follows from condition 1. Q.E.D.

Proof of Lemma 3. Suppose a bank is offered a price x, and the bank knows that it is type θ. If the bank sells the asset, it obtains $R(x)$. If the bank keeps the asset, it obtains $E[R(\theta + \tilde{\varepsilon})]$. Hence, the bank sells if and only if

$$R(x) \geq E[R(\theta + \tilde{\varepsilon})]. \qquad \text{(A-2)}$$

Observe that $E[R(\theta+\tilde{\varepsilon})] = \theta + r\Pr(\tilde{\varepsilon} \geq 1-\theta)$, and $R(x) = \begin{cases} x+r \text{ if } x \geq 1 \\ x \text{ if } x < 1 \end{cases}$. Hence, if $\theta \geq 1$, then $E[R(\theta+\tilde{\varepsilon})] \geq 1$, and so equation (A-2) can hold only if $x \geq 1$. In this case, equation (A-2) reduces to $x + r \geq \theta + r\Pr(\tilde{\varepsilon} \geq 1-\theta)$, which reduces to $x \geq \theta - r\Pr(\tilde{\varepsilon} < 1-\theta)$. If instead $\theta < 1$, then whenever $x \geq 1$, we clearly have $E[R(\theta+\tilde{\varepsilon})] < x + r$, so equation (A-2) holds; and if $x < 1$, equation (A-2) reduces to $x \geq \theta + r\Pr(\tilde{\varepsilon} \geq 1-\theta)$. Q.E.D.

Proof of Proposition 2. First observe that since $\theta_{\max} > 1$, the condition $\theta_{\max} - r\Pr(\tilde{\varepsilon} < 1-\theta_{\max}) \leq 1$ is equivalent to $\rho(\theta_{\max}) = 1$. Since $\rho(\theta)$ is increasing in θ, every type will agree to sell a price 1.

Consider any disclosure rule (g, S). If $\mu(s) \geq 1$, the market price will be $x(s) = \mu(s)$, and every type will sell. If $\mu(s) < 1$, the price must be below 1, since otherwise everyone will sell, and the market will lose money. But then only types below 1 may sell, and the proof of Part 3 in Lemma 4 implies that in equilibrium, no type sells upon receiving score s. Hence, Lemma 1 continues to hold, and the bank's ex-ante expected utility given disclosure rule (g, S) is the same as in Section 3. Hence, Proposition 1 continues to hold. Q.E.D.

Proof of Lemma 4

Part 1. The proof is by contradiction. Consider an optimal disclosure rule (S, g) and suppose there exists a type $\theta' \geq 1$ and a score $s' \in S$, such that $g(s'|\theta') > 0$ and such that type θ' does not sell its asset upon obtaining score s'.

Consider an alternate disclosure rule $(\tilde{S}, \tilde{g})$, in which we add a score $\tilde{s} \notin S$ that type θ' obtains instead of score s'. Specifically, $\tilde{S} = S \cup \{\tilde{s}\}$ and $\tilde{g}(s|\theta) = \begin{cases} g(s|\theta) \text{ if } \theta \neq \theta' \text{ and } s \neq s' \\ 0 \ \text{ if } \theta = \theta' \text{ and } s = s' \\ g(s|\theta) \text{ if } \theta = \theta' \text{ and } s = \tilde{s}. \end{cases}$. Under the alternate rule, the only type that obtains score $\tilde{s}$ is θ'. Hence, $x(s') = \theta'$. Since $\rho(\theta') \leq \theta'$, type θ' sells its asset upon obtaining score $\tilde{s}$. Hence, the alternate rule increases the probability that type θ invests in its project, while keeping the probabilities that each of the other types invests unchanged. Hence, the alternate rule increases the bank's ex ante expected utility. But this contradicts the optimality of the original disclosure rule (S, g).

Part 2. Consider an optimal disclosure rule (S, g) and suppose there exist a type $\theta \geq 1$ and a score $s \in S$, such that $g(s|\theta) \geq 0$. From part 1, we know that type θ sells the asset upon obtaining score s. Hence, $\rho(\theta) \leq x(s)$. From part 1, we also know that every type $\theta' > \theta$ such that $g(s|\theta') > 0$ sells. Finally, every type $\theta' < \theta$ such that $g(s|\theta') > 0$ sells, since $\rho(\theta') < \rho(\theta) \leq x(s)$. Hence, every type that obtains score s sells the asset upon obtaining the score. Consequently, selling does not convey any additional information to the market, and the market sets a price $x(s) = \mu(s)$, which is based only on the information that is contained in the score.

Part 3. The proof is by contradiction. (Note that it applies to the equilibrium that is induced by any disclosure rule, not necessarily the optimal.) Suppose that the highest type that obtains score s is less than 1 (that is, $g(s|\theta) = 0$ for every $\theta \geq 1$), and suppose that the equilibrium that is induced by disclosure rule g is such that some types sell upon obtaining score s. Denote the highest type that sells by θ'. ($\theta' < 1$.) The sale price must satisfy $x(s) \leq \theta'$, so that the market expected profits are non-negative. Since $\theta' < \rho(\theta') \leq 1$, we obtain that $x(s) < \rho(\theta')$. But this contradicts the fact that type θ' sells. Q.E.D.

Lemma A-2 *Assume that the bank observes its type. For every disclosure rule* (S, g) *that is optimal, we can construct a disclosure rule that induces the same probability that a bank of type* θ *sells its asset (and hence, is also optimal) but that uses at most* $k+1$ *scores,* $s_0, s_1, s_2, ..., s_k$ *such that when* $s_i \neq s_0$*, the highest type that obtains score* s_i *is type* θ_i*.*

Proof of Lemma A-2 Suppose (S, g) is an optimal disclosure rule. For every $i \in \{1, ..., k\}$, define $S_i = \{s : \mu(s) \in [\rho_i, \rho_{i-1})\}$, where $\rho_0 = \infty$. Let $(\tilde{S}, \tilde{g})$ be a disclosure rule with $k+1$ scores $\tilde{S} = \{s_0, s_1, s_2, ..., s_k\}$, such that for every $\theta \in \Theta$,

$$\tilde{g}(s_i|\theta) = \begin{cases} \sum_{s\in S_i} g(s|\theta) & \text{if } i \in \{1,2,..,k\} \\ \sum_{s\notin \cup_{i=1}^k S_i} g(s|\theta) & \text{if } i = 0 \end{cases}$$

Under disclosure rule (S, g), type $\theta_i \geq 1$ sells the asset upon obtaining score s if and only if $\mu(s) \geq \rho_i$. This happens with probability $\sum_{j=1}^{i} \sum_{s\in S_j} g(s|\theta)$. Type $\theta < 1$ sells if and only if $\mu(s) \geq \rho_k$, which happens with probability $\sum_{j=1}^{k} \sum_{s\in S_j} g(s|\theta)$. Following similar steps as in the proof of Lemma A-1, we obtain that (i) $\mu_{\tilde{g}}(s_0) < \rho_k$, and (ii) for every $i \in \{1, 2, ..., k\}$, $\mu_{\tilde{g}}(s_i) \in [\rho_i, \rho_{i-1})$. Hence, the probability that type θ sells the asset under disclosure rule $(\tilde{S}, \tilde{g})$ is the same as under disclosure rule (S, g). Q.E.D.

Lemma A-3 *Suppose banks know their types. For* $i \in \{1, ..., k\}$, *denote* $h_i(\theta) = \sum_{s\in S_i} g(s|\theta)$. *The planner's problem reduces to finding a set of functions* $\{h_i : \Theta \longrightarrow [0,1]\}_{i=1,...,k}$ *to maximize*

$$\sum_{\theta\in\Theta} p(\theta) \Pr(\tilde{\varepsilon} < 1-\theta) \sum_{i=1}^{k} h_i(\theta), \tag{A-3}$$

such that the following constraints hold:

(i) For every type $\theta \in \Theta$,

$$\sum_{i=1}^{k} h_i(\theta) \leq 1. \tag{A-4}$$

(ii) For every $i \in \{1, ..., k\}$,

$$\sum_{\theta\in\Theta} p(\theta)(\theta - \rho_i) h_i(\theta) \geq 0. \tag{A-5}$$

(iii) For every $i \in \{1, ..., k\}$, $h_i(\theta) = 0$ if $\theta > \theta_i$.

Proof of Lemma A-3. Maximizing the bank's ex-ante expected utility $\sum_{\theta\in\Theta} p(\theta)u(\theta|g)$ is equivalent to maximizing (A-3). (The proof is an extension of the proof of Lemma

2. More details to be added.) The first constraint says that the probability that a bank obtains a score $s \in \cup_{i=1}^{k} S_i$ is at most 1. The second constraint follows by summing the resource constraints for each $s \in S_i$. The third constraint follows from the definition of S_i. Q.E.D.

Lemma A-4 *If $E(\tilde{\theta}) < 1$, there must be a type $\theta' < 1$ that keeps its asset (i.e., obtains score s_0) with a positive probability.*

Proof of Lemma A-4. The proof is by contradiction. Consider the planner's problem in Lemma A-3. Suppose that no type obtains score s_0 with a positive probability; that is, $\sum_{i=1}^{k} h_i(\theta) = 1$ for every type $\theta \in \Theta$. Then since $\rho_i \geq 1$ for every $k \geq 1$, it follows that $\sum_{i=1}^{k} \sum_{\theta \in \Theta} p(\theta)(\theta - \rho_i)h_i(\theta) \leq \sum_{i=1}^{k} \sum_{\theta \in \Theta} p(\theta)(\theta - 1)h_i(\theta) = \sum_{\theta \in \Theta} p(\theta)(\theta - 1) \sum_{i=1}^{k} h_i(\theta) = E(\tilde{\theta}) - 1 < 0$. However, summing up all k resource constraints, we obtain $\sum_{i=1}^{k} \sum_{\theta \in \Theta} p(\theta)(\theta - \rho_i)h_i(\theta) \geq 0$. Hence, a contradiction. Q.E.D.

Lemma A-5 *If $E(\tilde{\theta}) < 1$, then under an optimal disclosure rule, all resource constraints are binding.*

Proof of Lemma A-5. The proof is by contradiction. Suppose (S, g) is an optimal disclosure rule and suppose there exists a score s, such that the highest type that obtains score s is θ_i and such that the resource constraint that is associated with score s is not binding; that is, $\sum_{\theta \in \Theta} p(\theta)(\theta - \rho_i)g(s|\theta) > 0$. Since $E(\tilde{\theta}) < 1$, we know from Lemma A-4 that there exists type $\theta' < 1$ that obtains score s_0 with a positive probability. Consider an alternate disclosure rule in which the planner reduces the probability that type θ' obtains score s_0 by a small Δ and increases the probability that type θ' obtains score s by Δ. The alternate rule increases the value of the objective function without violating any of the constraints. But this contradicts the optimality of the original disclosure rule. Q.E.D.

Proof of Proposition 3. Consider the planner's problem in Lemma A-3. We can assume, without loss of generality, that $\rho_1 > \rho_2 > ... > \rho_k$. We want to show that if $E(\tilde{\theta}) < 1$, then $h_i(\theta_i) = 1$ for every $i \in \{1, ..., k\}$. The proof is by contradiction. Suppose there exists $i \in \{1, ..., k\}$, such that $h_i(\theta_i) < 1$. From Lemma 4, we know that θ_i sells its asset with probability 1. Hence, there must be $j < i$, such that $h_j(\theta_i) > 0$. We obtain a contradiction by showing that there is an alternate solution that increases the value of the objective function in Lemma A-3 without violating the constraints.

Case 1: $\rho_j \geq \theta_i$. Consider alternating the original solution as follows: Reduce $h_j(\theta_i)$ by a small amount Δ and increase $h_i(\theta_i)$ by the same amount. Since $\rho_i \leq \theta_i$, increasing $h_i(\theta_i)$ weakly relaxes the resource constraint i, and since $\rho_j \geq \theta_i$, reducing $h_j(\theta_i)$ weakly relaxes the resource constraint j. In addition, at least one of these two constraints is strictly relaxed: if $\theta_i = 1$, then $\rho_j > \theta_i$, and constraint j is strictly relaxed; otherwise $\rho_i < \theta_i$, and constraint i is strictly relaxed. Finally, the value of the objective function and all other constraints remain unchanged. But this contradicts Lemma A-5.

Case 2: $\rho_j < \theta_i$. In this case, θ_i adds resources to the resource constraint j, and reducing $h_j(\theta_i)$ tightens the constraint. Since the resource constraint j is binding (Lemma A-5), there must be a type $\theta'' < \rho_j$, such that $h_j(\theta'') > 0$; this type takes resources from constraint j. Fix a small $\Delta > 0$ and let $\Delta' = \frac{p(\theta_i)(\theta_i - \rho_j)}{p(\theta'')(\rho_j - \theta'')}\Delta$; observe that $\Delta' > 0$. Consider an alternate solution in which for type θ_i, we reduce $h_j(\theta_i)$ by Δ but increase $h_i(\theta_i)$ by Δ, and for type θ'', we reduce $h_j(\theta'')$ by Δ' but increase $h_i(\theta'')$ by Δ'. Under the alternate rule, the probability that each type sells its asset remains unchanged, so the objective function remains unchanged. The resource constraint j remains unchanged since $-p(\theta_i)(\theta_i - \rho_j)\Delta - p(\theta'')(\theta'' - \rho_j)\Delta' = 0$. In contrast, since

$\rho_j > \rho_i$ (as $j < i$), the resource constraint i is loosened:

$$\begin{aligned}
p(\theta_i)(\theta_i-\rho_i)\Delta + p(\theta'')(\theta''-\rho_i)\Delta' &= p(\theta_i)(\theta_i-\rho_i)\Delta + p(\theta'')(\theta''-\rho_i)\frac{p(\theta_i)(\theta_i-\rho_j)}{p(\theta'')(\rho_j-\theta'')}\Delta \\
&> p(\theta_i)(\theta_i-\rho_i)\Delta + p(\theta'')(\theta''-\rho_j)\frac{p(\theta_i)(\theta_i-\rho_j)}{p(\theta'')(\rho_j-\theta'')}\Delta \\
&= p(\theta_i)(\theta_i-\rho_i)\Delta - p(\theta_i)(\theta_i-\rho_j)\Delta \\
&= p(\theta_i)(\rho_j-\rho_i)\Delta > 0.
\end{aligned}$$

All other constraints remain unchanged. But this contradicts Lemma A-5. Q.E.D.

Proof of Proposition 4. Consider the planner's problem in Lemma A-3. The proof is by contradiction. Suppose $(h_i)_{i=1,\ldots,k}$ is an optimal solution, such that $h_i(\theta) > 0$ for some type $\theta < 1$, and suppose, by contradiction, that there exists $\theta' < \theta$ and $j > i$, such that $h_j(\theta') > 0$. Assume, without loss of generality, that $\rho_j < \rho_i$.

Fix a small $\Delta > 0$, and let $\Delta' = \frac{p(\theta)(\theta-\rho_i)}{p(\theta')(\theta'-\rho_i)}\Delta$; observe that $\Delta' > 0$. Consider alternating the original solution as follows: For type θ, reduce $h_i(\theta)$ by Δ and increase $h_j(\theta)$ by Δ. For type θ', reduce $h_j(\theta')$ by Δ' and increase $h_i(\theta')$ by Δ'. Under the alternate rule, the probability that each type sells its asset remains unchanged, so the objective function remains unchanged. The resource constraint i remains unchanged since $-\Delta p(\theta)(\theta-\rho_i) + \Delta' p(\theta')(\theta'-\rho_i) = 0$. The resource constraint j is loosened since

$$\begin{aligned}
\Delta p(\theta)(\theta-\rho_j) - \Delta' p(\theta')(\theta'-\rho_j) &= \Delta p(\theta)(\theta-\rho_j) - \Delta\frac{p(\theta)(\theta-\rho_i)}{(\theta'-\rho_i)}(\theta'-\rho_j) \\
&= \Delta p(\theta)[(\theta-\rho_j) - \frac{(\theta-\rho_i)}{(\theta'-\rho_i)}(\theta'-\rho_j)] \\
&= \Delta p(\theta)\frac{(\theta-\rho_j)(\theta'-\rho_i)-(\theta-\rho_i)(\theta'-\rho_j)}{(\theta'-\rho_i)} \\
\Delta p(\theta)\frac{(\rho_i-\rho_j)(\theta'-\theta)}{(\theta'-\rho_i)} &> 0,
\end{aligned}$$

where the inequality follows since $\rho_i > \rho_j \geq 1 > \theta > \theta'$. All other constraints remain unchanged. So the alternate solution gives the same value for the objective but relaxes one of the resource constraints. But this contradicts Lemma A-5. Q.E.D.

Figure 1: The figure illustrates the reservation price $\rho(\theta)$ as a function of θ.

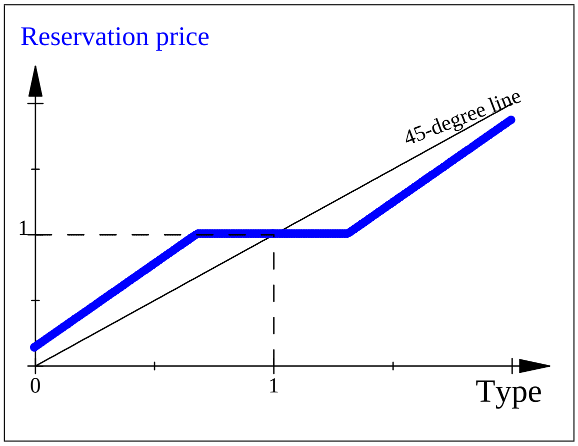
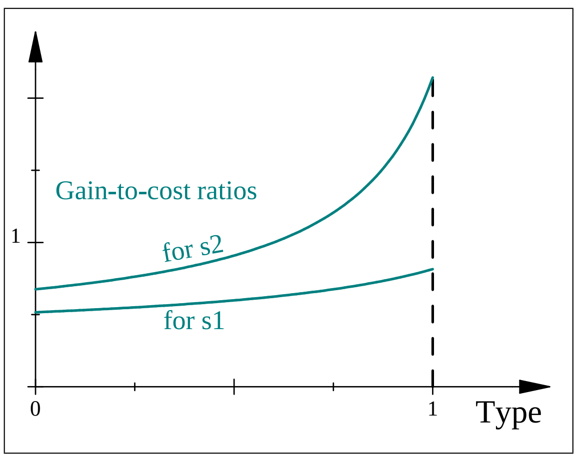


Figure 2: The figure illustrates the gain-to-cost functions that are associated with the highest score s_1 and the second highest score s_2.



Does Sovereign Credit Risk Affect Bank Lending? Evidence from Sovereign Rating Downgrades

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Abstract

We study the impact of sovereign credit risk on private credit. We exploit the asymmetric impact of sovereign downgrades on the ratings of banks at the sovereign bound versus banks below the bound due to sovereign ceiling policies followed by credit rating agencies. We show that sovereign downgrades lead to greater reductions in loan amounts and greater increases in loan spreads of banks at the sovereign bound relative to otherwise similar banks below the bound. Lending to foreign borrowers is also significantly affected, confirming a causal interpretation of the results. Our findings show that the transmission of risk from the sovereign to the financial sector has important effects on the supply of lending to the private sector.

JEL classification: E51, G21, G24, G28, H63

Keywords: Bank credit supply, Credit channel, Credit crunch, Credit ratings, Rating downgrades, Sovereign debt, Natural experiment

1. Introduction

While sovereign credit risk has been an important issue for emerging markets for a long time as these countries started to issue bonds in global markets, some of the most economically and financially developed countries in the world only recently saw their credit rating downgraded from the highest notation of AAA for the first time. For example, Standard & Poor's (S&P) downgraded the credit rating of the United States from AAA to AA+ in August 2011, and the rating of France from AAA to AA+ in January 2012 and then to AA in November 2013. In this paper, we address the question of whether deteriorating sovereign credit risk, as measured by credit ratings, cause reductions in bank lending supply to the private sector. This question is hard to answer because changes in sovereign credit risk are generally correlated with changes in macroeconomic and bank fundamentals that are also likely to impact private credit supply.

We employ a novel empirical strategy to study the effect of sovereign credit risk on bank lending supply. Sovereign ceiling policies followed by rating agencies provide a unique opportunity to identify the effects of sovereign credit risk on bank lending supply. These policies imply that bank credit ratings are bounded by country ratings. Following a sovereign rating downgrade, banks that have ratings at the sovereign bound are downgraded not necessarily because of a deterioration of their fundamentals, but because of the impact of the deterioration of the sovereign credit quality on the explicit and implicit guarantees provided by the government.[1]

We show that sovereign credit risk causally affects bank lending supply. We quantify the effects of sovereign rating downgrades on lending quantity and prices by comparing banks that have ratings at the sovereign bound prior to the downgrade (treatment group) with otherwise similar banks that

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[1] While credit rating agencies have been gradually moving away from a policy of never rating a firm above the sovereign, sovereign ratings remain a significant determinant of private credit ratings in recent data (Borensztein, Cowan, and Valenzuela (2013)). In practice, rating agencies follow a policy that banks cannot have a rating more than one-notch above the country rating.

have ratings below the sovereign bound (control group). While sovereign downgrades are likely to be accompanied by simultaneous macroeconomic shocks that affect the whole financial sector, we show that credit risk (measured by ratings) of the treatment group is affected *disproportionately more* than the control group by a sovereign downgrade. The benchmark empirical specification employs a difference-in-differences estimator that compares changes in the number of syndicated loans made by treated banks versus control banks during periods of sovereign downgrades.

We start the analysis by establishing that sovereign ratings lead to larger downgrades of (treated) banks that have ratings at the sovereign bound relative to (control) banks that have ratings below the sovereign bound. A sovereign downgrade leads to treated banks suffering a 1.5 notch larger rating reduction compared to banks rated below the sovereign bound. Furthermore, the probability of a rating downgrade as a consequence of a sovereign downgrade is significantly higher for treated banks than for control banks. We exploit this asymmetric effect of sovereign downgrades on the ratings of banks in the treatment and control groups in our analysis.

We next show that treated banks decrease lending in the quarter following the sovereign downgrade significantly more than control banks. The total number of new loans made by treated banks (as lead arranger or participant) decreases by about 30% more than that by control banks following sovereign downgrades. This relative decrease is also observed when we analyze the number of loans or the dollar volume of loans as lead arranger. In addition to the impact on quantities, sovereign downgrades also affect loan pricing. We find that treated banks increase interest rate spreads significantly more than control banks following sovereign downgrades. The differential effect in spreads is between 15 and 50 basis points. There is also a significant effect of sovereign downgrades on the extensive margin: the probability of making a new loan is about one percentage point lower for treated banks than for control banks, which represents about 15% of the unconditional probability of making a new loan at 7%.

One concern about difference-in-differences estimates is whether the treatment and control groups follow parallel trends prior to the treatment. We show that prior to the sovereign downgrade loan activity grows at about the same rate for both treated and control banks and we observe the relative decrease for the treatment group at exactly the time of the sovereign downgrade.

To address any remaining concerns about firms' demand for loans changing differentially for treated and control banks, as well as time-varying country-level factors that drive both bank loans and sovereign downgrades, we re-run our tests using a sample that includes only foreign borrowers (i.e., borrowers domiciled in countries other than the country of the lender). For this subsample, changes in demand for credit and changes in country-level factors caused by sovereign downgrades are unlikely to play any direct role. We find similar effects (both qualitatively and quantitatively) of sovereign downgrades on treated banks versus control banks for lending quantities and prices when we focus on foreign borrowers. This finding shows that the transmission of sovereign risk to the financial sector cross national boundaries, consistent with international transmission of liquidity shocks (Cetorelli and Goldberg (2012), Schnabl (2012)).

The identification strategy addresses three major identification challenges. First, a deterioration of macroeconomic fundamentals can cause sovereign downgrades, and simultaneously increase the cost of funding for banks and reduce the demand for loans on the part of borrowers. Reinhart and Rogoff (2009, 2011) and Laeven and Valencia (2012) document empirically that financial crises have large costs in terms of economic activity. This possibility is unlikely to contaminate our results because the treatment group contains higher rated banks that should be less sensitive to macroeconomic shocks than control banks. To further reduce concerns over this possibility, we control for changes in macroeconomic conditions using a large set of variables including public debt-to-GDP, GDP growth, inflation, private credit-to-GDP, indicators for crises (currency, inflation, sovereign debt, and banking), and recession indicators.

Second, sovereign downgrades may reduce both lending supply and demand. Supply is likely to decrease because of bank-specific liquidity shocks due to sovereign downgrades, but demand may contemporaneously fall because firm expectations about investment opportunities and returns are reduced, and their cost of capital is higher. Moreover, the identification strategy requires orthogonality between *ex-ante* bank health and borrower characteristics. It is possible that firms more affected by sovereign downgrades may borrow more from banks that are disproportionately more affected by the downgrade. Thus, we need to disentangle credit supply effects from credit demand effects. The identification strategy exploits the fact that, after controlling for potentially endogenous matching of borrowers and banks, treated banks have *higher* initial credit quality than control banks, and therefore are not likely to be more affected by a decrease in lending demand associated with sovereign downgrades in the same country and period.

To further reduce concerns over this possibility, the empirical tests control for a large set of observed pre-treatment lender and borrower characteristics, including lender size, profitability, capital-to-assets ratio, deposit-to-assets ratio and cash and marketable securities-to-assets ratio; borrower's size, Tobin's Q, leverage, tangibility, and credit rating; past lending relationships; and loan-specific controls. In addition, because lending can vary across firms and across banks for reasons that are not captured by the controls, we estimate models with bank- and bank-borrower fixed effects. This alleviates concerns about sample selection, such as bank-firm sorting (i.e., "good" firms borrow from "good" banks, or vice versa) and potential unobserved differences between firms that do and firms that do not take out bank loans during sovereign downgrades. Using a bank-borrower fixed effects approach, the effect of sovereign downgrades on bank lending is identified only by changes in lending within borrowers that take out loans from the same bank both before and after the sovereign downgrade. We also control for time trends using time fixed effects.

While the inclusion of controls in the regression addresses the fact that the groups being compared may have very different characteristics, the estimation of group differences may be improved by allowing for nonlinear and nonparametric methods. Thus, we also employ the Abadie and Imbens (2011) matching estimator of the average effect of the treatment on the treated (ATT). We isolate a (treated) bank with rating at the sovereign bound and then, from the population of (non-treated) banks with rating below the bound, look for control banks that best match the treated bank in multiple dimensions (covariates). The covariates are year, country, size, leverage, capital, deposits, and liquidity. All covariates are measured in the quarter prior to the sovereign downgrade. Using a difference-in-differences matching estimator, we find that treated banks, following a sovereign downgrade, cut lending significantly more than control banks.

Finally, it is difficult to disentangle sovereign-to-bank from bank-to-sovereign effects. Sovereign distress can trigger fragility in the banking sector due to direct holdings of government debt and explicit and implicit government guarantees (a "Greek" style crisis as emphasized in Gennaioli, Martin, and Rossi (2013a)). A distressed financial sector can force governments to bail out banks. Furthermore, the costs of these bailouts can result in a deterioration of the sovereign's creditworthiness, which feeds back to the financial sector due to banks' holdings of government bonds (an "Irish" style crisis as emphasized in Acharya, Drechsler, and Schnabl (2013)).

Our tests are designed to identify the causal effect of sovereign credit risk on financial sector credit risk, as the treatment group contains banks of higher quality and, therefore, they are less likely to require a government bailout. To further reduce concerns over the possibility that financial sector distress leads to sovereign's creditworthiness, we control for banking crises, banks' holdings of government debt, and the presence of "too big to fail" banks. We also conduct a placebo test in which we examine changes in bank loan for treated and control banks around banking crises that are not accompanied by sovereign downgrades. This placebo test can detect whether treated banks are more likely to require a bailout than control banks, which may confound our results. We find no difference between treated and control banks during banking crises that are not accompanied by sovereign downgrades, which supports a causal link from sovereign to bank credit risk.

We contribute to three strands of the literature. First, this paper is related to empirical work on the bank lending channel, in particular whether shocks to the financial position of a bank affect lending supply and real economic activity. The literature first used time-series correlation between changes in liquidity and changes in loans or output to show that liquidity shocks have real effects (Bernanke (1983), Bernanke and Blinder (1989)), but concerns about confounding macro effects have led to the use of cross-sectional variation in liquidity supply across banks (Kashyap, Lamont and Stein (1994), Kashyap and Stein (2000), Campello (2002), Aschcraft (2006), Ashcraft and Campello (2007)) or natural experiments (Peek and Rosengren (1997, 2000), Aschcraft (2005), Gan (2007), Khwaja and Mian (2008), Paravisini (2008), Chava and Purnanandam (2009)) to control for omitted variables. In particular, the 2007-2009 global financial crisis has been used as an experimental ground to study the effects of bank distress on private credit supply (e.g., Ivashina and Scharfstein (2010), Santos (2011), Iyer, Lopes, Peydro, and Schoar (2013)) and firm valuation, output and employment (Carvalho, Ferreira, and Matos (2013), Chodorow-Reich (2013)).

Second, this paper is related to the literature on the transmission of sovereign credit risk to the private sector. Gennaioli, Martin, and Rossi (2013a) show that sovereign defaults are followed by declines in private credit in countries where banks hold a significant share of their assets in government bonds due to collateral damage and financial institutions are more developed. Acharya, Drechsler, and Schnabl (2013) show that banks' bailouts triggered the rise of sovereign credit risk using credit default swaps (CDS) rates on European sovereigns and banks for 2007-2011. Moreover, changes in sovereign CDS explain changes in bank CDS in the post-bailout period, consistent with a loop between sovereign and bank credit risk. Others papers study empirically the effects of sovereign credit risk on corporate credit risk (Durbin and Ng (2005), Borensztein, Cowan, and

Valenzuela (2013), Bedendo and Colla (2013)), foreign borrowing (Arteta and Hale (2008), Ağca and Celasun (2012)), and investment (Almeida, Cunha, Ferreira, and Restrepo (2013)).[2]

Finally, we contribute to the literature on credit ratings. Research shows that credit ratings contain information not imbedded in prices of corporate bonds and stocks (e.g., Hand, Holthausen, and Leftwich (1992), Goh and Ederington (1993)).[3] Ratings are also shown to affect a firm's cost of capital (Kisgen and Strahan (2010)) and corporate decisions such as capital structure (Faulkender and Peteresen (2006), Kisgen (2006, 2007, 2009)), and investment (Sufi (2009), Lemmon and Roberts (2010), Chernenko and Sunderam (2012), Harford and Uysal (2013)). Our findings complement this literature by establishing empirically that exogenous changes in banks' credit ratings affect bank lending supply.

To the best of our knowledge, our paper is the first to provide a causal estimate of the effect of sovereign credit risk on bank lending supply. A distinct aspect of our empirical strategy is that the bank rating downgrades that we use to identify lending effects are caused by sovereign downgrades and ceiling policies followed by rating agencies, and are thus unrelated to variation in bank fundamentals. Treated banks are of higher quality than control banks, which helps to rule out several alternative explanations to our results such as confounding economy-wide shocks. Thus, we establish that the effect on bank lending can be plausibly attributed to the bank lending channel, and not to the firm borrowing channel. Credit ratings downgrades can also directly affect bank's access to wholesale funding and public bond markets because of regulations and policies followed by market participants such as pension funds. Furthermore, we can attribute the effect to a direct sovereign-to-bank channel unrelated to banks' holdings of government bonds and bailouts. Our

[2] Researchers have also studied the stock and bond market reaction to sovereign rating downgrades (Brooks, Faff, Hillier, and Hillier (2004), Gande and Parsley (2005), and Ferreira and Gama (2007)).

[3] Recent papers, however, show that credit ratings are not a sufficient statistic for risk in structured finance markets, in particular during the 2007-2009 financial crises (e.g., Adelino (2009), Griffin and Tang (2012), and He, Qian, and Strahan (2012)).

findings suggest that public debt management has important effects on bank lending supply and governments should be aware of the potential adverse effects of deteriorating sovereign credit risk on private credit markets.

Our focus on the consequences of sovereign risk deterioration to the financial sector has important policy implications. Our findings show that changes in sovereign risk can spread to the financial sector and thus reduce private credit supply and increase private borrowing costs. The existent global financial architecture based on national-based financial safety nets, backstops and supervision strengths the sovereign-bank link, impairing monetary policy transmission and exacerbating economic downturns. This issue is at the heart of the discussion of the establishment of a European Banking Union, which would help to delink sovereigns and banks and restore proper transmission of monetary policy.

2. Methodology and Data

In this section we first describe our experimental design and difference-in-differences estimator. We exploit the fact that sovereign ratings downgrades create exogenous variation in bank credit ratings because of sovereign ceilings as a way to identify the effect of sovereign credit risk on bank lending. We then describe the data sources, sample and variables used in this study.

2.1. Quasi-Natural Experiment: Sovereign Ceiling and Downgrade

Credit rating agencies play an important role in providing information about the ability and willingness of issuers, including governments and private issuers, to meet their financial obligations. The three major agencies -- Standard and Poor's (S&P), Moody's and Fitch -- assign different types or ratings depending on the maturity (short term or long term) and currency denomination of an issuance (foreign currency or local currency).

Credit rating agencies usually do not grant private issuer a credit rating higher than the rating given to the sovereign bonds of the country where the firm is domiciled, a policy usually referred to as a sovereign ceiling. Although the sovereign ceiling policy has been gradually relaxed by the credit rating agencies starting in 1997 and some private issuers receive ratings higher than country they are located in, rating agencies recognize that the sovereign rating is still an important consideration in determining private issuer ratings. Standard & Poor's (2012) reports that only 113 private issuers and local and regional government ratings exceed the rating on the sovereign in the country of domicile, on a foreign-currency basis. Consistent with this policy, Borensztein, Cowan, and Valenzuela (2013) show that rating agencies have gradually moved away from a policy of never rating a private company above the sovereign (the sovereign ceiling), but it appears that sovereign ratings remain an important determinant of the credit rating assigned to the private sector.

In the case of banks, the fact that governments often act as emergency liquidity providers (backstops) to domestic banks in distress, by providing bailouts in times of crisis (O'Hara and Shaw (1990), Gorton and Huang (2004), Brown and Dinc (2005), Laeven (2011) , Duchin and Sosyura (2012), Philippon and Schnabl (2013)), provides a strong economic rationale for a sovereign ceiling policy. Standard & Poor's (2012) reports that there are only 3 commercial banks (Gulf International Bank, Banco Espanol de Credito, Banco Santander) worldwide with rating that exceeds the sovereign, on a foreign-currency basis, as of October 2012.[4]

This study focuses on the foreign-currency, long-term issuer ratings, where agencies use a sovereign's rating as a strong upper bound on the credit ratings of firms that operate within each country. We prefer the S&P foreign currency long-term rating history over other agencies' rating history because S&P tends to be more active in making rating revisions, and tends to lead other agencies in re-rating (Kaminsky and Schmukler (2002), Gande and Parsley (2005)). Foreign currency rating announcements by S&P also seem to convey a greater own-country stock market impact and

[4] There are also a number of subsidiaries and branches of banks located mainly in Ireland with ratings above the sovereign. These cases are not considered in this study as we run the analysis at the parent bank level.

seem not to be fully anticipated by the market (Reisen and von Maltzan (1999), Brooks, Faff, Hillier, and Hillier (2004)). S&P is also the agency least likely to assign corporate ratings above the sovereign rating.

Because of the sovereign ceiling policy, there are different predictions for the effect of a sovereign downgrade on banks that have pre-downgrade ratings at the sovereign bound (treated banks) and those that have rating below the sovereign bound (control banks). The effect of a sovereign downgrade on treated banks' ratings should be much larger, potentially reaching a one-for-one effect, than the one on control banks as the sovereign ceiling is non-binding for the latter. For example, if a country with an AAA rating is downgraded to AA+, banks with ratings of AAA are much more likely to be downgraded than otherwise similar banks with rating below AAA before the sovereign downgrade. Our identification strategy uses this asymmetry in the relation between bank ratings and sovereign ratings to pin down the effect of changes in sovereign credit risk on bank lending. This asymmetry helps to distinguish the effects of credit ratings from confounding common macro effects, as macro shocks associated with sovereign downgrades should affect all banks equally. If there were any differential macro effects, better quality banks (the treatment group) should not be more affected than lower quality banks (the control group), controlling for differences in borrower characteristics.

2.2. Data

The loan market data come from the Thomson Reuters Dealscan database. Dealscan collects loan-level information on syndicated loans, including the identity of the lead arranger and participant banks and the borrower, as well as a variety of loan contract terms (amount, all-in drawn spread, maturity, structure, purpose, and type). The sample covers all loans initiated from January 1, 1982 to December 31, 2012. Syndicated loan deals include multiple tranches (or loan facilities) that differ in price, type, and maturity (such as a line of credit and a term loan). Following Qian and Strahan

(2007), Santos (2011) and others, we perform tests at the facility level; that is, we treat the facilities in each deal as different loans. In the case of facilities with multiple participants and lead arrangers, we consider each facility multiple times to capture differences across the participants and lead arrangers.

In the loan-level tests, the outcomes variables are the log of the *Loan Amount* in U.S. dollars (Dealscan item Facility Amount) and the *Loan Spread* over the LIBOR rate (Dealscan item All-in Spread Drawn). We measure the impact on loans in the treatment and control groups using a six month window before the loan date, i.e., if there has been a sovereign downgrade in the six month period prior to the loan date. We obtain similar estimates using a three-month or 12-month window.

We use several loan characteristics as control variables in the regression tests. *Secured* is a dummy variable that takes the value of one if loan is secured by collateral, and zero otherwise (DealScan item Secured). *Senior* is a dummy variable that takes the value of one if loan is senior, and zero otherwise (DealScan item Seniority). Dummy variables for the *Purpose* of the loan (DealScan item Primary Purpose) – general purpose, debt repayment, working capital, and takeover. *Term Loan* is a dummy variable that takes the value of one if the loan is a term loan and zero if the loan is a credit line (DealScan item Specific Tranche Type). *Dividend Restriction* is a dummy variable that takes the value of one loan if loan has restrictions on paying dividends, and zero otherwise (DealScan item Covenants: General-Material Restriction). *Prior Participant* and *Prior Lead* are dummy variables that take the value of one if the bank served as a participant banks and lead arranger bank, respectively, for the borrower's previous loan.

We match the (parent) lender in Dealscan (lead arranger and participant banks) to Bloomberg using banks' country, ticker and name.[5] We obtain both the lender credit rating and its country (sovereign) credit rating using S&P long-term foreign currency issuer-level credit rating. Sovereign

[5] We treat loans granted by a parent bank and loans granted by a subsidiary or a branch of this bank as loans originating from the same lead arranger. For example, we classify loans arranged by bank branches like Santander Brasil and wholly owned subsidiaries like Abbey National as loans made by Banco Santander.

and bank ratings are mapped into 22 numerical categories, with 22 corresponding to the highest rating (AAA) and one to the lowest (default) – See Table A1 in the Internet Appendix for detailed conversion. We also match the (parent) lender to Bankscope using banks' country, ticker and name to obtain bank characteristics. The final sample is restricted to lenders that have a credit rating because our identification strategy exploits shocks to the lender credit rating due to sovereign downgrades. We are able to obtain lender ratings and characteristics for 91% of the total amount of loans.[6]

We use several bank characteristics as control variables in the regression tests. Bank controls are measured prior to the loan facility date.[7] *Size* is defined as the log of total assets in billions of U.S. dollars (Bankscope item 2025). *Profitability* is proxied by return on assets (ROA), defined as operating income divided by total assets (Bankscope item 4024). *Capital* is defined as the ratio of common equity (Bankscope item 2055) to total assets. *Liquidity* is the ratio of cash and marketable securities (Bankscope item 2075) to total assets. *Deposits* is the ratio of deposits and short-term funding (Bankscope item 2030) to total assets. We also control for bank's nationality using country fixed effects or unobserved time-invariant bank heterogeneity using bank fixed effects.

In addition, we control for several time-varying bank country effects (at the annual frequency): *GDP Growth*, *Inflation Rate*, and *Private Credit-to-GDP* taken from the World Bank/World Development Indicators database. *Public Debt-to-GDP* and indicators for *Crises* (currency, inflation, sovereign debt external and internal, and banking) are taken from the Reinhart and Rogoff (2009) data up to 2010. OECD *Recession* indicators for each country drawn from the Federal Reserve Economic Data (FRED) database.[8] *Bank Bondholdings* proxies for domestic banks' holdings of public

[6] We obtain similar estimates when we include unrated banks in the control group.
[7] When Bankscope reports more than one record for each lender-year we choose the record giving preference to consolidated accounts, IFRS/IAS standards, and Audited accounts.
[8] The recession indicators are available for 38 countries with monthly frequency and we adopt the definition from the "Period following the Peak through the Trough" definition. We aggregate the monthly series into an annual series and classify a country as being in a recession in a given year if it has more than six months of recession.

debt using financial institutions' net claims to the government relative to their total assets, following Kumhof and Tanner (2008) and Gennaioli, Martin, and Rossi (2013a), taken from the International Monetary Fund/International Financial Statistics database.[9]

We match the borrowers in Dealscan to the WRDS-Factset Fundamentals Annual Fiscal (North America and International) and Compustat databases to obtain borrower characteristics. The Factset database contains firms from 80 countries for the 1982-2012 period. We use the Dealscan-Compustat linking table to obtain identifiers (ISIN, SEDOL, CUSIP) from Compustat.[10] We use these identifiers to match the borrower to the corresponding entity in Factset. For those borrowers without a match, we search for a match between Dealscan and Factset using company ticker, country and name. We are able to obtain borrower characteristics for 81% of the total amount of loans.[11]

We use several borrower characteristics as control variables in the regression tests taken from Factset and Compustat. Borrower controls are measured prior to the loan facility date. *Size* is defined as the log of total assets (Factset item FF_ASSETS, Computstat item AT). *Tobin's Q* is defined as the ratio of total assets plus market capitalization (Factset item FF_MKT_VAL, Computstat item CSHO x PRCC_F) minus common equity (Factset item FF_COM_EQ, Computstat item CEQ) to total assets. *Leverage* is defined as the ratio of total debt (Factset item FF_DEBT, Computstat items DLC+DLTT) to total assets. *Tangibility* is defined as the ratio of net property, plant and equipment (Factset item FF_PPE_NET, Computstat item PPNT). *Unrated* is a dummy variable that takes the value of one if a borrower does not have a credit rating, and *Rating* is the credit rating mapped into 22 numerical categories, with 22 corresponding to the highest rating (AAA) and one to the lowest (default); rating is the borrower's S&P long-term foreign currency

[9] In the case that a country variable is missing for some countries, we assume it takes the value of zero and add indicators for missing variables to the regression.
[10] We thank Michael Roberts for providing the Dealscan-Compustat match, used in Chava and Roberts (2008).
[11] The majority of the unmatched loans correspond to private borrowers.

issuer rating taken from Bloomberg. We also control for firm fixed effects or bank-firm fixed effects. The bank-firm fixed effect alleviates concerns about sample selection, such as potential unobserved differences between firms that did and firms that did not take out bank loans around sovereign downgrades. The effect of sovereign downgrades on loan amounts and spreads is identified only by the changes within firms that took out loans from the same bank both before and after the sovereign downgrade.

To address any remaining concerns with demand-side effects, in some tests, we restrict the sample to foreign loans; i.e., loans in which the bank nationality is different from borrower's country of domicile. These tests using only foreign borrowers are a powerful way to rule out demand-driven effects in our tests.

Using the loan facility-level data, we aggregate the data to run regression tests by lender-quarter and lender-borrower quarter. In the lender-quarter panel, the outcome variables measure the level of activity of each bank in the syndicated loan market in each quarter between the first quarter in which the bank made a loan and the last quarter plus four quarters.[12] In a quarter with no loan activity by a lender we assume that the loan activity variables take the value of zero. We measure the impact on loan activity in the treatment and control groups two-quarter after the sovereign downgrade because banks are already committed to some loans signed before the sovereign downgrade. We obtain similar point estimates but with less precision when we measure the effect in the quarter immediately following the sovereign downgrade.

We first calculate the *Total Number of Loans* made by a bank (as participant or lead arranger) in each quarter. The lead arranger banks of each loan facility usually hold the largest share of the syndicated loans (see Kroszner and Strahan (2001) and Sufi (2007)). The lead arranger is frequently the administrative agent, with a fiduciary duty to other syndicate members to provide timely

[12] We assume that a bank is not active in the syndicated loan market if it does not make any loan during the four quarters after the quarter of the last loan made as reported in the Dealscan database.

information about the default of the borrower. For these reasons, we also calculate the *Number of Loans as Lead* in each quarter only taking into account loans in which the bank acted as lead arranger. An alternative measure of loan activity is given by the *Amount of Loans as Lead* made in each quarter by a bank as lead arranger. The Dealscan database rarely reports the actual loan shares of an individual lead arranger bank in a loan, so we instead use pro-rata shares. If a bank is a sole lead arranger, it gets a 100% share of the loan, and if there are M lead arrangers, each gets $1/M$ share of the loan.

We also run tests using growth rates of loans around sovereign downgrades using the lender-quarter panel. The growth rate is defined as the percentage change of a loan activity variable (*Growth of the Total Number of Loans*, *Growth of the Number of Loans as Lead, Growth of the Amount of Loans as Lead*) from the quarter prior to the sovereign downgrade to two quarter after the sovereign downgrade. We also run some tests using as an alternative a lender-borrower-quarter panel dataset that allows us to control for borrower heterogeneity. The outcome variables measure the number of syndicated loans for each bank-firm pair (i,j) in each quarter between the first quarter in which bank i made a loan (as a lead arranger or as a participant) to borrower j and the last quarter that we observe a loan for each pair, plus the five subsequent years, which is the typical maturity of a syndicated loan. In a quarter with no loans in a bank-firm pair we assume that the variable takes the value of zero. We calculate the *Total Number of Loans* (as participant or lead arranger) and the *Number of Loans as Lead* (only as lead arranger) in each bank-firm pair and quarter. Because there are many observations with a zero, we restrict the sample to bank-firm pairs with at least one loan as lead arranger over the sample period. Additionally, we run the tests using a logit regression model in which the dependent variable is an indicator that takes the value of one if the variable *Total Number of Loans* (or *Number of Loans as Lead*) is strictly positive.

2.3. Summary Statistics

The sample covers 933,126 loan facilities taken out by 60,436 borrower firms from 480 lenders (participants or lead arrangers) between 1982 and 2012. The sample is restricted to lenders with a credit rating. If we restrict the sample to lead arrangers only, we have 629,594 loan facilities taken out by 58,250 firms from 473 lead arrangers. There are 230,147 lender-borrower pairs in this sample, of which 133,152 have at least two loans (33,980 firms and 443 banks).

Table 1 provides summary statistics (mean, median, standard deviation, minimum, maximum, and number of observations) for the lender-quarter panel that we use in the main tests. Panel A provides statistics for all observations, and Panel B provides statistics for observations where the bank has a rating at the sovereign bound.

The average bank has a credit rating of 16.6 and a median rating of 17 which corresponds to a rating of A on the S&P scale. The highest rated banks have a rating of AAA and the lowest rated banks are in default. In about 20% of the lender-quarter observations in the sample the rating of the bank is equal to or above the rating of the sovereign in the quarter prior to the sovereign downgrade (of which 17% are exactly at the sovereign bound). The data includes a sovereign downgrade in about 2% of the lender-quarter observations. Table A2 in the Internet Appendix provides further detail on the countries and timing of sovereign downgrades.

Panel A of Table 1 show summary statistics of the outcome variables at the quarterly frequency: *Total Number of Loans*, *Number of Loans as Lead*, and *Amount of Loans as Lead*. We consider separately all loans and only loans made to foreign borrowers (*Foreign*). Banks make over 50 loans on average in a quarter, with a median of 10 loans. The distribution is highly skewed, with a maximum of 1,122 loans. Banks make just over 34 loans as lead arrangers, and the median number of loans made by a bank as a lead arranger is five. The amount of loans in which the bank acts as lead arrangers in a quarter is about $2.5 billion on average, with a median of $100 million. The growth rate of the total number of loans is, on average, 17%, with a median of zero. The growth rate is similar, though lower (average at 12% and median at -1%), for the number of loans in which the bank acts as a lead arranger.

Banks participate in a significant number of loans outside of their own country. On average, banks make 27 loans to foreign borrowers in a quarter (19 as lead arrangers), although the median is just two (one as lead arrangers).

Given that we are relying on syndicated loans, it is not surprising that banks are, on average, large, with total assets of about $200 billion, with a median of $62 billion. The smallest bank in the sample has assets of about $100 million, whereas the largest bank has just under $3 trillion in total assets. The return on assets of banks is on average 1%, with a median of also 1%. The common equity ratio (*Capital*) is 12% of assets with a median of 8%, which is in line with regulatory requirements. Cash and marketable securities (*Liquidity*) represent about 19% of assets and deposits and short-term funding (*Deposits*) about 66%, on average.

Panel B shows that banks with a rating at the sovereign bound make fewer loans per quarter (median of 3 loans versus 10 for the full sample) and also act as lead arranger on fewer loans (median is 2 versus 5 for the full sample). The difference is smaller, though in the same direction, when we look only at loans made to foreign borrowers. These banks are also somewhat smaller than those in the full sample with median assets just under $50 billion. The fact that these banks appear smaller and less active in the syndicated loan market than those in the full sample is due to a composition effect, and would be reversed if we consider differences within a country.

The final two rows of Table 1 show summary statistics for the outcome variables in the loan-level data set (*Loan Amount* and *Loan Spread*). The average dollar amount of the loans in the sample is $509 million (with a median of $156 million), and the average loan spread is about 180 basis points. We see similar spreads, but smaller loans (average of $374 million and median of $110 million) for loans made by banks with a rating at the sovereign bound.

Table A2 in the Internet Appendix shows the number of banks that have a rating at the sovereign bound (i.e., rating greater than or equal to the sovereign rating) in the quarter prior to the sovereign downgrade. The countries that appear most prominently are Argentina (mostly due to the 2000-2001 crisis), Egypt, Greece, Italy, Japan, and Spain. The treated observations are distributed evenly over the late 1990s, peak in 2001 and 2002, and then rise again significantly between 2008 and 2012 at the time of the global financial crisis and Eurozone sovereign debt crisis. We have a total of 447 lender-quarter observations with a sovereign downgrade, of which 110 observations (of which 89 are exactly at the sovereign bound and 21 above the bound) correspond to banks that have a rating at the sovereign bound prior to the sovereign downgrade. These observations include 53 unique treated banks. This percentage is consistent with the one in Panel B of Table A.1 that in about 20% of the lender-quarter observations the bank has a rating at the sovereign bound.

3. Results

3.1. Bank Ratings and Sovereign Downgrades

The first test we perform considers the effect of sovereign downgrades on the rating of banks that are at the sovereign bound (the treated banks) in the quarter prior to the treatment (the sovereign downgrade) versus banks below the bound (the control banks). We measure the impact on ratings in treatment and control groups in the quarter of the sovereign downgrade. We run OLS specifications using the lender-quarter panel and standard errors are clustered at the lender country-level to correct for within-country residual correlation. We estimate a difference-in-differences regression of bank rating (converted to a numerical scale) on sovereign downgrade, where the explanatory variable of interest is the interaction of the *Sovereign Downgrade* dummy with and a dummy for treated banks (*Lender Rating* >= *Sovereign Rating*). The regression equation is as follows:

$$LenRat_{it} = \beta_1 1_{LenRat_{i,t-1} >= SovRat_{i,t-1}} + \beta_2 1_{SovDowngrade_t} \quad (1)$$

$$+ \beta_3 1_{LenRat_{i,t-1} >= SovRat_{i,t-1}} 1_{SovDowngrade_t} + \beta_4 X_{i,t-1} + \eta_t + \eta_i + \varepsilon_{it}$$

where $X_{i,t-1}$ is a vector of lender controls (*Size*, *Profitability*, *Capital*, *Liquidity* and *Deposits*) and time-varying (lender) country controls (see data section), η_t are quarter fixed effects, and η_i are either country or lender fixed effects. The coefficient of interest β_3 measures the extent to which higher rated banks (those that we call treated) suffer more with the sovereign downgrade than lower rated banks due to the sovereign ceiling policy followed by rating agencies. The larger impact of the sovereign downgrade on higher quality banks is important to help us distinguish the effect of the sovereign downgrade on bank lending from alternative hypotheses: a reduction in demand for bank loans from corporations in the same country; reverse causality (i.e., the possibility that it is the deterioration of the risk of banks that causes the sovereign downgrade); and confounding macro effects.

Table 2 presents the estimates of regression equation (1). Column (1) includes only (lender) country and quarter fixed effects, whereas the column (2) includes bank controls and time-varying macroeconomic country controls. We find that, on average, a sovereign downgrade leads to treated banks suffering a 1.4 to 1.5 notch larger rating reduction compared to banks rated below the sovereign bound. The treated bank indicator (*Lender Rating* >= *Sovereign Rating*) is associated with a rating that is approximately 3 notches higher than the other banks in the same country (as we would expect, by construction of how we define treated banks), and the *Sovereign Downgrade* dummy is associated with lower ratings of about 0.5 to 0.9 notches. The effects are all significant at the 5% level. We include lender fixed effects in columns (3) and (4), and the differential effect between treated and control banks is slightly reduced to about 1 to 1.2 notches, but still highly significant in both specifications. Table A3 in the Internet Appendix shows consistent results using a logit model for the probability of a bank being downgraded. Treated banks are again much more likely to be downgraded than control banks; the marginal probability of a rating downgrade is 12 percentage points higher for treated banks versus control banks.

Figure 1 shows how the effect of sovereign downgrades on treated banks' ratings evolves over time relative to control banks from four years before the sovereign downgrade and up to four years after that. The estimates in this figure come from the same regression in column 2 of Table 2, but we replace the interaction term with dummies for whether a bank-quarter will be in the treated group *t* years ahead, or was in the treated group *t* years before. The figure shows that treated banks have somewhat higher ratings three or four years before the downgrade but then there is no significant changes in the two years prior to the sovereign downgrade. The treated banks then suffer a significantly larger downgrade at the time of the sovereign downgrade and this difference persists for up to two years afterwards. The effect reverses about three years after the sovereign downgrade, suggesting that our experiment is exploiting a temporary shock that lasts about two years. We will return to the issue of the duration of the shock in the next section.

Overall, the evidence in this section shows an important asymmetry in the reaction of bank credit ratings to sovereign downgrades between the treatment and control groups due to the sovereign ceiling. This asymmetry is the basis of our identification strategy to identify supply effects in credit markets and a direct sovereign-to-bank effect.

3.2. Bank Lending and Sovereign Downgrades

3.2.1. Effect by Lender and Quarter

We now turn to the impact of the sovereign downgrade on measures of bank lending. The first set of tests considers difference-in-differences estimates of a sovereign downgrade on the number and amount of loans made by treated banks (those with a pre-downgrade rating at the sovereign bound) *relative* to control banks (those with a pre-downgrade rating below the sovereign bound). We measure the impact on loan activity in treatment and control groups two-quarter after the sovereign downgrade because banks are already committed to some loans signed before the sovereign downgrade.

We run OLS specifications using the lender-quarter panel and standard errors are clustered at the lender country-level to correct for within-country residual correlation. We estimate a difference-in-differences regression of bank lending on sovereign downgrade, where the explanatory variable of interest is the interaction of the *Sovereign Downgrade* dummy with and a dummy for treated banks (*Lender Rating* >= *Sovereign Rating*). The regression equation is as follows:

$$Lending_{it} = \beta_1 1_{LenRat_{i,t-1} >= SovRat_{i,t-1}} + \beta_2 1_{SovDowngrade_t} + \beta_3 1_{LenRat_{i,t-1} >= SovRat_{i,t-1}} 1_{SovDowngrade_t} + \beta_4 X_{i,t-1} + \eta_t + \eta_i + \varepsilon_{it} \quad (2)$$

where the *Lending* variable is the log of one plus *Total Number of Loans*, *Number of Loans as Lead*, and *Amount of Loans as Lead* and other variables are defined as in equation (1). The coefficient of interest is β_3, which tests the hypothesis that treated banks cut lending more following a sovereign downgrade than control banks.

Table 3 shows the results, where all columns include quarter fixed effects, as well as lender fixed effects, which takes into account overall time trends in the data, as well as fixed differences between lenders. We find that treated banks show a large and statistically significant reduction in the total number of loans, the number of loans where they act as leads, and the total dollar amount of the loans where they act as lead arrangers following a sovereign downgrade. All the dependent variables are in logs so the coefficients in the table can be interpreted as growth rates.

The first column of Table 3 shows that the interaction term (*Lender Rating* >= *Sovereign Rating* × *Sovereign Downgrade*) coefficient is -0.31 and is significant at the 1% level, which indicates that banks in the treatment group make about 30% fewer loans as a result of the sovereign downgrade relative to the control group. The estimated differential reduction in lending activity is approximately 26% in column (2) when we include bank controls as well as time-varying country macro controls. We see a similar reduction for the number of loans where the bank acts as the lead arranger. The reduction in the amount lent (as lead arranger) suffers a more drastic than the results for the number of loans suggest. In fact, treated banks cut the amount lent by 81 to 83% relative to control banks (the point estimates in the two regressions that use the log of *Amount of Loans as Lead* as the dependent variable are approximately -1.6 to -1.8.

The next columns in Table 3 show our estimates when we restrict the sample to loans to foreign borrowers. Any effects of a sovereign downgrade on bank lending to foreign borrowers are very unlikely to be explained to a reduction in the demand for credit. The estimates are qualitatively similar, but reduced in magnitude and statistical significance when we consider this subset of loans. On average, treated banks reduce the number of loans they make by about 11% to 20%. As before, the impact on the amount of loans is more severe, with the point estimate suggesting a reduction of about 90% relative to the control group.

In terms of the control variables, the coefficients have the expected sign. Larger banks make, on average, significantly more loans and lend larger total amounts, as do more profitable banks and banks that are better capitalized.

A concern about inferences from the treatment-effects framework is whether the processes generating the treatment and control group outcomes followed parallel trends prior to the treatment. Differences in the post-treatment period can only be attributed to the treatment when this assumption holds. The best way to address this concern is to look at the evolution of the outcome variables measuring loan activity in the years leading to the treatment separately for the treatment and control groups.

Figure 2 shows the equivalent of columns (2) and (8) in Table 3 where the dependent variable is *Total Number of Loans*, with the interaction term of sovereign downgrade and the indicator for treated banks (*Lender Rating* >= *Sovereign Rating*) replaced with yearly leads and lags of this interaction. The specification is otherwise identical to the one used in Table 3. Figure 2 shows that, in the four years prior to the sovereign downgrade, the treated banks were making about the same (or somewhat higher) total number of loans per quarter as the control group. We then we see a significantly lower number of loans in the year of the downgrade and the subsequent year, and then the difference reverts to close to zero by the second year after the downgrade. Similarly, treated banks show no differences relative to control banks in the number of loans made to foreign borrowers, with a sharp difference emerging in the year of the downgrade and persisting for the two subsequent years. This figure looks essentially the same if we consider the number of loans made as a lead arranger instead of all loans.

Thus, it is hard to argue that the lending processes of banks in the two groups follow different trends before the downgrade. Furthermore, we can see that lending falls dramatically for the treatment group in the year of the sovereign downgrade versus the control group.

Table 4 performs a similar analysis to the one in Table 3, but using the percentage growth (as in Chodorow-Reich (2013)) of the number and total dollar amount of loans by bank and by quarter (*Growth Total Number of Loans*, *Growth Number of Loans as Lead, Growth Amount of Loans as Lead*). In these specifications, growth rates are computed from the quarter prior to the sovereign downgrade to two quarters after the downgrade. All regressions include quarter and country fixed effects and time-varying country macro controls in some specifications. Table A4 in the Internet Appendix presents similar estimates when we include quarter and lender fixed effects.

The sovereign downgrade reduces growth rates by 30 to 40 percentage points more for treated banks versus control banks in the sample of all loans and the sample of foreign loans. This compares to an average growth rate of 16%, which means that, consistent with the previous table, treated banks suffer an economically large reduction in the number of loans relative to control banks. The estimate also reflects the fact that many banks just exit altogether (implying a growth rate of -100%). We expand on this issue when we discuss the results at the lender-borrower-quarter level.

3.2.2. Matching Estimator

Our benchmark specification uses a parametric regression where the outcome difference for the group of interest versus other observations is estimated by the coefficient on the group dummy. The regression model is specified according a linear representation of the outcome variable. Bank controls such as size, return on assets and capital ratio and fixed effects are added to the specification to capture additional sources of banks heterogeneity. However, the inclusion of controls in the regression per se does not address the fact that the groups being compared may have very different characteristics (Heckman, Ichimura, Smith, and Todd (1998), Roberts and Whited (2010)). Moreover, when control variables have poor distributional overlap, estimation of group differences can be improved by allowing for nonlinear and nonparametric methods.

We use in alternative a nonparametric strategy. We conduct our analysis combining a natural experiment with the use of matching estimators. The idea of this estimator is to first isolate treated observations (in our application, banks with rating at the sovereign bound) and then, from the population of non-treated observations, find observations that best match the treated ones in multiple dimensions (covariates). In this framework, the set of counterfactuals are restricted to the matched controls. In other words, it is assumed that in the absence of the treatment (in our application, sovereign downgrades), the treatment group would behave similarly to the control group. The matches are made so that treated and control observations have distributions for the covariates that are as similar as possible to each other, in the pre-downgrade period.

We employ the Abadie and Imbens (2011) estimator, as implemented by Abadie, Drukker, Herr, and Imbens (2004). The Abadie-Imbens matching estimator minimizes the distance (the Mahalanobis distance) between a vector of observed covariates across treated and non-treated banks, finding control banks based on matches for which the distance between vectors is the smallest. The estimator allows control banks to serve as matches more than once, which compared to matching without replacement, lowers the estimation bias but can increase the variance. In our estimations we select four matched control observation for each treated observation. The Abadie-Imbens estimator produces exact matches on categorical variables. Naturally, the matches on continuous variables will not be exact (though they should be close). The procedure recognizes this difficulty and applies a bias-correction component to the estimates of interest. In addition, the estimator produces heteroskedastic robust standard errors.

Among the list of categorical variables that we include in our estimates are quarter and bank country. Our non-categorical variables include banks' *Size*, *Profitability*, *Capital*, *Liquidity* and *Deposits*. The estimates implicitly account for all possible interactions between the included covariates.

We estimate the average effect of the treatment on the treated (ATT). We model the outcomes in our experiments in differenced form by performing difference-in-differences estimations. Specifically, rather than comparing the outcome variables (*Growth Total Number of Loans*, *Growth Number of Loans as Lead*, and *Growth Amount of Loans as Lead*) of the treatment and control groups, we compare the changes in the outcome variables between the groups around the sovereign downgrade. We do so because loan activity of the treated and controls could be different prior to the event defining the experiment, and continue to be different after that event, in which case our inferences could be potentially biased by these uncontrolled bank-specific differences.

Panel A of Table 5 compares mean and median of the covariates between the 46 treated lender-quarters and the remaining 184 control lender-quarters (i.e., lenders that are not assigned to the treatment group) in the quarter prior to the sovereign downgrade. The Pearson chi-square statistic tests for differences in the medians of the variables of interest between the treatment and control groups prior to treatment. After the matching procedure, there are still statistically significant differences in the pre-downgrade median values of the covariates across treatment and control groups. The median *Profitability*, *Capital* and *Liquidity* are higher for banks in the treatment versus the control group. These differences, however, cannot explain our findings since we expect banks with higher return on assets, capital ratio and liquid assets to be less affected, rather than more affected by the sovereign downgrade. In addition, these differences are economically small. Panel A also compares the entire distributions of the various matching covariates (pre-treatment) across the two groups of firms using the Kolmogorov-Smirnov test of distributional differences. Similarly to the median tests, there are statistical significant differences in the covariates between treated and control banks.

Panel B of Table 5 shows that treated banks decrease loan activity as measured by percentage growth in the number of loans significantly more than control banks in the two-quarter after the sovereign downgrade versus the quarter prior to the downgrade. We present both the difference-in-difference estimate and the ATT estimate with bias correction. The ATT is -27 percentage points, which is highly statistically and economically significant. The magnitude of the ATT is even stronger when the outcome variables are the percentage growth in number of loans and amount of loans as lead arranger at more than 50 percentage points. Table 5 shows similar estimates when we consider the sample of loans made to foreign borrowers. The ATT is statistically significant for the total number of loans and number of loans as lead arranger, while it is imprecisely estimated for the amount of loans as lead arranger.

3.2.3. Loan-Level Effects

The results in the previous subsection are obtained using lender-quarter observations. This allows us to consider the percentage growth in the number of loans and the number and amount of loans made by a bank in each quarter. While we are able to control for a number of time varying and time invariant lender-specific and country characteristics, the previous analysis does not allow us to control for borrower and loan characteristics. One remaining concern is that, even though we are comparing banks with a higher quality (as proxied by credit ratings) to banks with lower quality, treated banks might experience a larger drop in demand for loans than banks in the control group.

The outcome variables in loan-level analysis are the amount of each loan, as well as the loan spread. We measure the impact on *Loan Amount* and *Loan Spread* in treatment and control groups in the six-month period after the sovereign downgrade. We obtain similar estimates when we use a three-month or one-year window. Previous studies (e.g., Khwaja and Mian, 2011) find no effects on loan pricing due to disruptions to bank liquidity. They authors argue that the number of loans is more likely to be the margin of adjustment for banks. We revisit this issue by testing whether shocks to bank ratings due to sovereign downgrades impact the pricing of loans made by affected banks.

We run OLS specifications using the loan-level data set and standard errors are clustered at the bank country-level to correct for within-country residual correlation. In this setting, we control for time varying borrower characteristics. In addition, we also perform tests with lender by borrower fixed effects, which means we estimate all our effects within each lender-borrower pair. This specification eliminates any concerns that endogenous lender-borrower matching might drive our results. Using a bank-borrower fixed effects approach, the effect of sovereign downgrades on bank lending is identified only by changes in lending within borrowers that take out loans from the same bank both before and after the sovereign downgrade. The regression equation for a loan facility of lender i (participant or lead arranger bank) and borrower j in year t is as follows:

$$Loan\ Amount(Spread)_{ijt} = \beta_1 1_{LendRat_{i,t-1} \geq SovRat_{i,t-1}} + \beta_2 1_{SovDowngrade_t} + \beta_3 1_{LendRat_{i,t-1} \geq SovRat_{i,t-1}} 1_{SovDowngrade_t} + \beta_4 X_{i,t-1} + \beta_5 X_{j,t-1} + \eta_t + \eta_{ij} + \varepsilon_{it} \quad (3)$$

where $X_{i,t-1}$ is a vector of lender controls and time-varying (lender) country controls (the same controls as in Tables 3 and 4), $X_{j,t-1}$ is a vector of borrower controls, η_t are year fixed effects, and η_{ij} are lender-borrower pair fixed effects.[13] The coefficient of interest is β_3, which tests the hypothesis that sovereign downgrades lead treated banks to decrease loan amounts and increase interest rate spreads more than control banks. As before, we also perform all of our tests in the subsample of foreign borrowers, which further reduces the possibility that local demand shocks might explain the effects on bank lending.

Panel A of Table 6 shows the results for the log of *Loan Amount* and *Loan Spread* in the sample of all borrowers. The results show that loans made by treated banks are about 15% to 24% smaller than loans made by control banks following a sovereign downgrade. All these results are consistent with the previous two tables where we saw a sharp reduction in the amount lent by treated banks. Column (3) includes loan-level controls such as *Secured*, *Senior*, *Purpose*, *Term Loan*, *Dividend Restriction*, *Prior Participant*, and *Prior Lead*. We add the loan controls separately because they are jointly determined with both loan amount and loan spread, so we want to make sure that our estimates do not change much when we add these controls. The interaction coefficient in column (3) is similar to that in column (2).

Panel A of Table 6 also shows strong effects of the sovereign downgrade on loan spreads in the sample of all borrowers. The effect is about 45 basis points with no lender controls, and it gets reduced to 17 to 20 basis points when the regressions include lender and loan controls. All these

[13] All point estimates are basically unchanged when we use quarter fixed effects, but the variance covariance matrix becomes highly singular in this setup.

estimates are statistically significant at the 5% level. The impact on loan spreads represents between 11% and 25% of the average loan spread in the sample.

When we restrict sample to foreign borrowers (Panel B of Table 6), we find an interesting asymmetry between the results for loan amounts and for loan spreads, again consistent with the findings in Khwaja and Mian (2011). We find that the differential effect on the loan amount of treated banks versus control banks in the sample of foreign borrowers has about the same magnitude as in the sample of all borrowers, i.e., a drop of 11% to 19%. However, we find no differential effects on the pricing of loans made by treated banks relative to control banks in the sample of foreign borrowers. The point estimates are economically small, at between zero and 3 basis points, and they are not statistically significant. This suggests that banks are more likely to act as price takers, or at least have less influence on the pricing of loans when they deal with foreign borrowers relative to domestic ones.

Table A5 in the Internet Appendix shows that the results are almost unchanged if we exclude borrowers in the financial sector (SIC codes 6000-6999) or public sector (SIC codes 9000-9999).

3.2.4. Lender-Borrower-Quarter Effects

In our last set of tests, we use the lender-borrower-quarter panel to assess how the probability of observing a loan for a given lender-borrower pair changes for treated banks versus control banks as a consequence of the sovereign downgrade. This panel extends the lender-quarter tests as it allows to control for borrower heterogeneity as we do in the loan level tests.

We run logit regression models where the dependent variable is a dummy that takes the value of one if there is at least one loan in a lender-borrower pair and quarter in which the lender is a participant (*Total Number of Loans* dummy) or lead arranger (*Number of Loans as Lead* dummy). Standard errors are clustered at the bank country-level to correct for within-country residual correlation. All regressions include quarter and lender-borrower fixed effects.

Table 7 shows the results. Panel A shows the results for the sample of all borrowers and Panel B for the sample of foreign borrowers. We find a statistically significant negative effect in the probability of observing a loan in a given quarter for a given lender-borrower pair for treated banks versus control banks. The effect is similar when we define the dependent variable using the total number of loans or the number of loans as lead arrangers. The reduction in marginal probability is approximately 0.9-1.1 percentage points, for an unconditional probability of observing a loan in a given quarter for each lender-borrower pair of about 7%.[14] We obtain similar estimates in columns (2) and (4) when we include lender and borrower controls as well as time-varying (lender) country macro controls. The magnitude of the effect is similar in the sample of all borrowers and the sample of foreign borrowers.

We conclude that the sovereign downgrades have significant adverse bank lending channel effects both on the intensive and extensive margins. The intensive margin effects are a reduction in the amount of lending and an increase in interest rate spreads to firms borrowing at the time sovereign downgrade. The extensive margin effects consist in a reduction in the probability of obtaining a new loan following a sovereign downgrade.

3.2.5. Identifying the Sovereign-to-Bank Effect

Our experiment – the asymmetric impact of sovereign rating downgrades on banks at the sovereign bound versus banks below the sovereign bound – is well suited to identify the effect of sovereign credit risk on bank lending. While the reverse effect (i.e., deteriorating bank credit quality can lead to sovereign downgrades) is an important (Acharya, Drechsler, and Schnabl (2013) and Strahan (2013)), this is not the channel that our setting is picking up, as higher-quality banks are more affected than lower-quality banks by the sovereign downgrade. If bank credit risk leads to

[14] We are not able to compute marginal effects in the logit models due to the large number of fixed effects, so the marginal effects are obtained from a linear probability model that we run with the same controls.

sovereign credit downgrades, this effect is more likely to be driven by lower-quality than higher-quality banks. Additionally, we include indicators for banking crises in our specifications. To address any remaining concerns about a bank-to-sovereign effect driving our results, we implement the tests described below.

First, in order to further isolate the impact of sovereign credit risk on the banking sector, we perform tests that focus on a sample of banks that are *not* "too big to fail". Following Demirgüç-Kunt and Huizinga (2010), we define banks as "too big to fail" if they are above the 75th percentile of the distribution of the ratio of bank total liabilities (Bankscope item 11750) to GDP. The threshold (9.7% of bank liabilities to GDP) matches closely the 10% threshold used in Demirgüç-Kunt and Huizinga (2010).

We re-run the lender-quarter level tests in Table 3 (the dependent variables are *Total Number of Loans*, *Number of Loans as Lead, Amount of Loans as Lead*) and Table 4 (the dependent variables are the corresponding percentage growth of *Total Number of Loans*, *Number of Loans as Lead, Amount of Loans as Lead* around a sovereign downgrade) excluding from the sample banks that are "too big to fail", which may be included in our treatment group. We only present the estimates using the most complete specifications, including lender-specific and country controls as well as lender and quarter fixed effects. Panel A of Table 8 shows that the results are similar to those of Tables 3 and 4, indicating that banks with higher systemic risk do not explain our results.

Second, we perform lender-quarter panel regression tests using a sample of countries that have high creditor rights. Gennaioli, Martin, and Rossi (2013a) predict that the effect of sovereign credit risk on banks should be larger in countries where creditor rights are better protected (see Corollary 2 of Gennaioli et al. for a detailed discussion of this prediction). Thus, if a sovereign-to-bank effect explains our results, we should find more pronounced effects of sovereign downgrades on the sample of (lender) countries with high creditor rights. We split the sample of countries into those above and below the median country-level creditor rights measure constructed by Djankov, McLiesh, and Shleifer (2007). Consistent with the results in Gennaioli, Martin, and Rossi (2013a), Panel B of Table 8 shows that our estimates of the differential effect of sovereign downgrades are amplified in magnitude in countries with above median creditor rights. Table A6 in the Internet Appendix shows that the results are also consistent when we re-run the tests in Table 8 using the sample of foreign borrowers.

In alternative to study sample splits, we re-run the lender-quarter level tests including the "too big fail" bank-level indicators and high creditor rights country-level indicators as additional control variables. We also check whether our findings are driven by state-owned banks by including a bank-level *Government Owned* indicator, which takes the value of one if the percentage (direct and indirect) of government ownership is above 50% (the data source is Bankscope). There are 44 government-owned banks in our sample, which correspond to about 10% of the number of unique banks. Table A7 in the Internet Appendix shows that our results are barely affected when we include these additional controls.

Third, we perform a placebo test that aims to directly address the issue of whether our results are driven by banking crises, and the impact of deteriorating bank credit quality on sovereign credit risk. We replicate exactly the same experiment that we run for sovereign downgrades but using a placebo period. That is, we use bank and sovereign credit ratings to sort banks into treatment and control groups. Treated banks are those that have pre-treatment rating above the sovereign bound. In this placebo, we create a *Banking Crisis* indicator, in alternative to the *Sovereign Downgrade* indicator that is equal to one if a country suffers a banking crisis that is not accompanied by a sovereign rating downgrade in the last four quarters. We then re-run the lender-quarter level tests in Tables 3 and 4. Table 9 shows the results of this placebo test. Panel A presents the results for the sample of all borrowers and Panel B for the sample of foreign borrowers. The negative treatment-control difference in bank lending outcomes does not appear in banking periods that are not accompanied by sovereign downgrades as shown by the statistically insignificant coefficient on the interaction term *Lender Rating >= Sovereign Rating* × *Banking Crisis* in most specifications. If anything, we observe that treated banks are *less* affected in banking crises than control banks (see columns (1) and (2) of Panel A). This falsification test helps to rule out alternative explanations for our results, in particular a bank-to-sovereign effect, and gives further support to a direct effect of deteriorating sovereign credit quality on financial institutions.

Finally, we show that banks' holdings of government debt do not explain our results. Gennaioli, Martin, and Rossi (2013a) and Acharya, Drechsler, and Schnabl (2013) show that sovereign distress can trigger fragility in the banking sector due to direct holdings of government debt. In our main tests, we control for country-level bank holdings of government bonds. To further rule out this possibility, we re-run the lender-quarter tests using bank-level total holdings of government securities, including treasury bills, bonds and other government securities (Bankscope item 29272) divided by total assets, as an additional control (*Government Bondholdings*). The mean of the *Government Bondholdings* variable is 6% (among positive reported holdings), which is in line with the figures reported in Gennaioli, Martin, and Rossi (2013b).[15] They find that government bondholdings are accumulated in normal times, but there is some further accumulation of bonds during sovereign debt crises among the larger and more profitable banks. While government bondholdings are associated with higher loans consistent with a liquidity view (i.e., banks bought more bonds in the past to tap future investments opportunities), they do not seem to affect bank lending at the time of sovereign defaults.[16] Table A8 in the Internet Appendix report the estimates including *Government Bondholdings* as control, which are consistent with the main findings of a decrease in bank lending

[15] We assume that the holdings of government securities are zero in the case the variable is missing.
[16] Gennaioli, Martin, and Rossi (2013b) find that the government bondholdings accumulated during the crisis do not impair bank lending, but the stable component of bondholdings has a negative effect on bank lending at the time of sovereign defaults.

following a sovereign default. Moreover, we find that the coefficient on *Government Bondholdings* is positive, which is consistent with the liquidity view.

The total holding of government securities variable from Bankscope does not break down government bonds by nationality, in particular the banks' holdings of own-government bonds. To better control for the bank's holdings of government bonds, we collect bank-level data on holdings of different sovereign government bonds released as part of the bank stress tests conducted for Eurozone banks as of December 2010 by the European Banking Authority (EBA). Acharya, Drechsler, and Schnabl (2013) document a significant home bias in banks' holdings of sovereign bonds, as 70% of the average bank's sovereign bonds (roughly one-sixth of its risk-weighted assets) were in the local sovereign bonds. We re-run the lender-quarter tests using a sample of 54 Eurozone banks in 2008-2012 and including the gross direct long exposures to own country (bonds and loans), divided by total assets, as an additional control variable (*Exposure to Own Country*). The mean of the *Exposure to Own Country* variable is 11%, which is in line with the figures reported in Acharya, Drechsler, and Schnabl (2013). Table A9 in the Internet Appendix report these estimates. We still find that the coefficient of the interaction *Lender Rating* >= *Sovereign Rating* × *Banking Crisis* is negative, but it is imprecisely estimated due to a much smaller sample size (about 800 lender-quarter observations). The *Exposure to Own Country* coefficient is negative but statistically insignificant.

4. Conclusion

We study the impact of sovereign credit quality on the supply of bank credit by exploiting the exogenous variation in bank ratings created by sovereign downgrades because of sovereign ceiling policies adopted by rating agencies. We show that banks with ratings at sovereign rating bound prior to the sovereign downgrade reduce lending volume and increase interest rate spreads significantly more than otherwise similar banks with ratings below the sovereign bound. An important feature our empirical strategy is that the ratings downgrades that we use to identify bank lending effects can be plausibly attributed to the bank lending channel, and not to the firm borrowing channel, and are unrelated to variation in bank-specific characteristics. Additionally, treated banks are of higher quality than control banks, which rules out several alternative explanations to our results such as confounding economy-wide and bank-to-sovereign effects associated with sovereign downgrades should affect all banks equally. Results relying exclusively on loans to foreign borrowers and a placebo test confirm

Our findings show that the sovereign-to-bank effect for the transmission of credit risk has important effects on private credit markets. Public debt management has important effects on credit markets through sovereign rating downgrades and ceilings, and not only through fundamentals such as interest rates and crowding-out effects. When the sovereign has a credit rating that is not at the high end of the scale, credit ratings for banks from that country will tend to suffer, regardless of their health, with deteriorating sovereign credit quality. Governments should be aware of the potential adverse effects of rating announcements on credit markets and they should factor these negative externalities into their borrowing decisions.

References

Abadie, Alberto, and Guido W. Imbens, 2011, Bias-Corrected Matching Estimators for Average Treatment Effects, *Journal of Business and Economic Statistics* 29, 1–11.

Abadie, Alberto, David Drukker, Jane Leber Herr, and Guido W. Imbens, 2004, Implementing Matching Estimators For Average Treatment Effects in Stata, *Stata Journal* 4, 290–311.

Acharya, Viral, Itamar Drechsler, and Philipp Schnabl, 2013, A Pyrrhic Victory? Bank Bailouts and Sovereign Credit Risk, *Journal of Finance*, forthcoming.

Adelino, Manuel, 2009, How Much Do investors Rely on Ratings? The Case of Mortgage-Backed Securities, Working paper, Duke University.

Ağca, Senay, and Oya Celasun, 2012, Sovereign Debt and Corporate Borrowing Costs in Emerging Markets, *Journal of International Economics* 88, 198-208.

Almeida, Heitor, Igor Cunha, Miguel Ferreira and Felipe Restrepo, 2013, The Real Effects of Credit Ratings: Using Sovereign Downgrades as a Natural Experiment, Working paper, Nova School of Business and Economics.

Arteta, Oscar, and Galina Hale, 2008, Sovereign Debt Crises and Credit to the Private Sector., *Journal of International Economics* 74, 53–69.

Ashcraft, Adam B., 2005, Are Banks Really Special? New Evidence from the FDIC-Induced Failure of Healthy Banks, *American Economic Review* 95, 1712–1730.

Ashcraft, Adam, 2006., New Evidence on the Lending Channel., *Journal of Money, Credit and Banking* 38, 751–776.

Ashcraft, Adam, and Campello, Murillo, 2007, Firm Balance Sheets and Monetary Policy Transmission, Journal of Monetary Economics 54, 1515–1528.

Bedendo, Mascia, and Paolo Colla, 2013, Sovereign and Corporate Credit Risk: Spillover Effects in the Eurozone., Working paper, Università Bocconi.

Bernanke, Ben, 1983, Nonmonetary Effects of the Financial Crisis in the Propagation of the Great Depression, *American Economic Review* 73, 257–276.

Bernanke, Ben, and Alan Blinder, 1989, Credit, Money, and Aggregate Demand, *American Economic Review* 78, 435–439.

Borensztein, Eduardo, Kevin Cowan, and Patricio Valenzuela, 2013, Sovereign Ceilings Lite? The Impact of Sovereign Ratings on Corporate Ratings in Emerging Market Economies., *Journal of Banking and Finance* 37, 4014–4024.

Brooks, Robert, Robert William Faff, David Hillier, and Joseph Hillier, 2004, The National Market Impact of Sovereign Rating Changes., *Journal of Banking and Finance* 28, 233–250.

Brown, Craig and Serdar Dinc, 2005, The Politics of Bank Failures: Evidence from Emerging Markets, *Quarterly Journal of Economics* 120, 1413–1444.

Campello, Murillo, 2002, Internal Capital Markets in Financial Conglomerates: Evidence from Small Bank Responses to Monetary Policy, *Journal of Finance* 57, 2773–2805.

Carvalho, Daniel, Miguel Ferreira, and Pedro Matos, 2013, Lending Relationships and the Effect of Bank Distress: Evidence from the 2007-2008 Financial Crisis, *Journal of Financial and Quantitative Analysis*, forthcoming.

Cetorelli, Nicola, and Linda Goldberg, 2012., Banking Globalization and Monetary Transmission., *Journal of Finance* 67, 1540–6261.

Chava, Sudheer, and Michael Roberts, 2008, How Does Financing Impact Investment? The Role of Debt Covenants, *Journal of Finance* 63, 2085–2121.

Chava, Sudheer, and Purnanandam, Amiyatosh, 2011, The Effect of Banking Crisis on Bank-Dependent Borrowers, *Journal of Financial Economics* 99, 116–135.

Chernenko, Sergey, and Adi Sunderam, 2012, The Real Consequences of Market Segmentation, *Review of Financial Studies* 25, 2041–2069.

Chodorow-Reich, Gabriel, 2013, The Employment Effects of Credit Market Disruptions: Firm-level Evidence from the 2008-09 Financial Crisis, *Quarterly Journal of Economics*, forthcoming.

Demirguc-Kunt, Asli, and Huizinga, Harry, 2010, Are Banks Too Big to Fail or Too Big to Save? International Evidence from Equity Prices and CDS Spreads, CEPR Discussion Papers 7903.

Djankov, Simeon, and Caralee McLiesh, and Andrei Shleifer, 2007, Private Credit in 129 Countries, *Journal of Financial Economics* 84, 299–329.

Duchin, Ran, and Denis Sosyura, 2012, The Politics of Government Investment, *Journal of Financial Economics* 106, 24–48.

Durbin, Erik, and David Ng, 2005, The Sovereign Ceiling and Emerging Market Corporate Bond Spreads, *Journal of International Money and Finance* 24, 631–649.

Faulkender, Michael, and Mitchell Petersen, 2006, Does the Source of Capital Affect Capital Structure? *Review of Financial Studies* 19, 45–79.

Ferreira, Miguel, and Paulo Gama, 2007, Does Sovereign Debt Ratings News Spill Over to International Stock Markets? *Journal of Banking and Finance* 31, 3162–3182.

Gan, Jie, 2007, The Real Effects of Asset Market Bubbles: Loan- and Firm-Level Evidence of a Lending Channel, *Review of Financial Studies* 20, 1941–1973.

Gande, Amar, and David Parsley, 2005, News Spillovers in the Sovereign Debt Market, *Journal of Financial Economics* 75, 691–734.

Gennaioli, Nicola, Alberto Martin, and Stefano Rossi, 2013a, Sovereign Default, Domestic Banks, and Financial Institutions., *Journal of Finance*, forthcoming.

Gennaioli, Nicola, Alberto Martin, and Stefano Rossi, 2013b, Banks, Government Bonds and Default: What Do the Data Say, Working paper, Purdue University.

Goh, Jeremy, and Louis Ederington, 1993, Is a Bond Rating Downgrade Bad News, Good News, or No News for Stockholders? *Journal of Finance* 48, 2001–**20**08.

Gorton, Gary, and Lixin Huang, 2004, Liquidity, Efficiency, and Bank Bailouts, *American Economic Review* 94, 455–483.

Griffin, John, and Dragon Tang, 2012, Did Subjectivity Play a Role in CDO Credit Ratings? *Journal of Finance* 67, 1293–1328.

Hand, John, Robert Holthausen, and Richard Leftwich, 1992, The Effect of Bond Rating Agency Announcements on Bond and Stock Prices, *Journal of Finance* 47, 733–752.

Harford, Jarrad, and Vahap Uysal, 2013, Bond Market Access and Investment, *Journal of Financial Economics*, forthcoming.

He, Jie, Jun Qian, and Philip Strahan, 2012, Are All Ratings Created Equal? The Impact of Issuer Size on the Pricing of Mortgage-Backed Securities, Journal of Finance 67, 2097–2137.

Heckman, James, Hidehiko Ichimura, Jerey Smith, and Petra Todd, 1998, Characterizing Selection Bias Using Experimental Data., *Econometrica* 66, 1017–1098.

Ivashina, Victoria and David Scharfstein, 2008, Bank Lending During the Financial Crisis of 2008, *Journal of Financial Economics* 97, 319–338.

Iyer, Rajkamal, Samuel Lopes, José-Luis Peydró, and Antoinette Schoar, 2013, The Interbank Liquidity Crunch and the Firm Credit Crunch: Evidence from the 2007-09 Crisis, *Review of Financial Studies* 27, 347–372.

Kaminsky, Graciela, and Sergio Schmukler, 2002, Emerging Market Instability: Do Sovereign Ratings Affect Country Risk and Stock Returns? *World Bank Economic Review* 16, 171–195.

Kashyap, Anil, and Jeremy C. Stein, 2000, What Do a Million Observations on Banks Say About the Transmission of Monetary Policy? *American Economic Review* 90, 407–428.

Kashyap, Anil, Owen Lamont, and Jeremy Stein, 1994, Credit Conditions and the Cyclical Behavior of Inventories., *Quarterly Journal of Economics* 109, 565–592.

Khwaja, Asim, and Atif Mian, 2008, Tracing the Impact of Bank Liquidity Shocks, *American Economic*

Review 98, 1413–1442.

Kisgen, Darren, 2006, Credit Ratings and Capital Structure, *Journal of Finance*, 61, 1035–1072.

Kisgen, Darren, 2007, The Influence of Credit Ratings on Corporate Capital Structure Decisions, *Journal of Applied Corporate Finance*, 19, 65–73.

Kisgen, Darren, 2009, Do Firms Target Credit Ratings or Leverage Levels? *Journal of Financial and Quantitative Analysis* 44, 1323–1344.

Kisgen, Darren, and Philip Strahan, 2010, Do Regulations Based on Credit Ratings Affect a Firm's Cost of Capital? *Review of Financial Studies*, 23, 4324–4347.

Kroszner, Randall, and Philip Strahan, 2001, Bankers on Boards: Monitoring Conflicts of Interest, and Lender Liability, *Journal of Financial Economics* 62, 415–452.

Kumhof, Michael, and Evan Tanner, 2008, Government Debt: A Key Role in Financial Intermediation, in Reinhart, Carmen M., Carlos Végh, and Andres Velasco, eds.: *Money, Crises and Transition*, Essays in Honor of Guillermo A. Calvo.

Laeven, Luc, 2011, Banking Crises: A Review, *Annual Review of Financial Economics* 3, 17–40.

Lemmon, Michael, and Michael Roberts, 2010, The Response of Corporate Financing and Investment to Changes in the Supply of Credit, *Journal of Financial and Quantitative Analysis* 45, 555–587.

O'Hara, Maureen, and Wayne Shaw, 1990, Deposit Insurance and Wealth Effects: The Value of Being "Too Big to Fail", *Journal of Finance* 45, 1587–1600.

Paravisini, Daniel, 2008, Local Bank Financial Constraints and Firm Access to External Finance, *Journal of Finance* 63, 2161–2194.

Peek, Joe, and Eric Rosengren, 1997, The International Transmission of Financial Shocks., *American Economic Review* 87, 495–505.

Peek, Joe, and Eric Rosengren, 2000, Collateral Damage: Effects of the Japanese Bank Crisis on Real

Activity in the United States, *American Economic Review* 90, 30–45.

Philippon, Thomas, and Philipp Schnabl, 2013, Efficient Recapitalization., *Journal of Finance* 68, 1–42.

Qian, Jun, and Philip Strahan, 2007, How Laws and Institutions Shape Financial Contracts: The Case of Bank Loans, *Journal of Finance* 62, 2803–2834.

Reinhart, Carmen, and Kenneth Rogoff, 2009, *This Time Is Different: Eight Centuries of Financial Folly* (Princeton University Press).

Reinhart, Carmen, and Kenneth Rogoff, 2011, From Financial Crash to Debt Crisis, *American Economic Review* 101, 1676–1706.

Reisen, Helmut, and Julia von Maltzan, Julia, 1999, Boom and Bust and Sovereign Ratings, *International Finance* 2, 273–293.

Roberts, Michael, and Toni Whited, 2010, Endogeneity in Empirical Corporate Finance, *Handbook of the Economics of Finance* 2, 493-572.

Santos, João, 2011, Bank Corporate Loan Pricing Following the Subprime Crisis, *Review of Financial Studies* 24, 1916–1943.

Schnabl, Philipp, 2012, The International Transmission of Bank Liquidity Shocks: Evidence from an Emerging Market, *Journal of Finance* 67, 897–932.

Strahan, Philip, 2013, Too Big to Fail: Causes, Consequences, and Policy Responses, *Annual Review of Financial Economics* 5, 43–61.

Standard & Poor's, 2012, Corporate and Government Ratings that Exceed the Sovereign Rating, October.

Sufi, Amir, 2007, Information Asymmetry and Financing Arrangements: Evidence from Syndicated Loans, *Journal of Finance* 62, 629–668.

Tang, Tony, 2009, Information Asymmetry and Firms' Credit Market Access: Evidence from Moody's Credit Rating Format Refinement, *Journal of Financial Economics* 93, 325–351.

Figure 1 – Bank Rating and Sovereign Downgrade

This figure shows point estimates and 95 percent confidence intervals for the effect over time of a sovereign downgrade on the rating of a bank that has a rating equal to or above the sovereign. The dependent variable is the S&P rating of the bank converted to a numeric scale. Controls are those from Table 2. Standard errors are clustered at the country level.

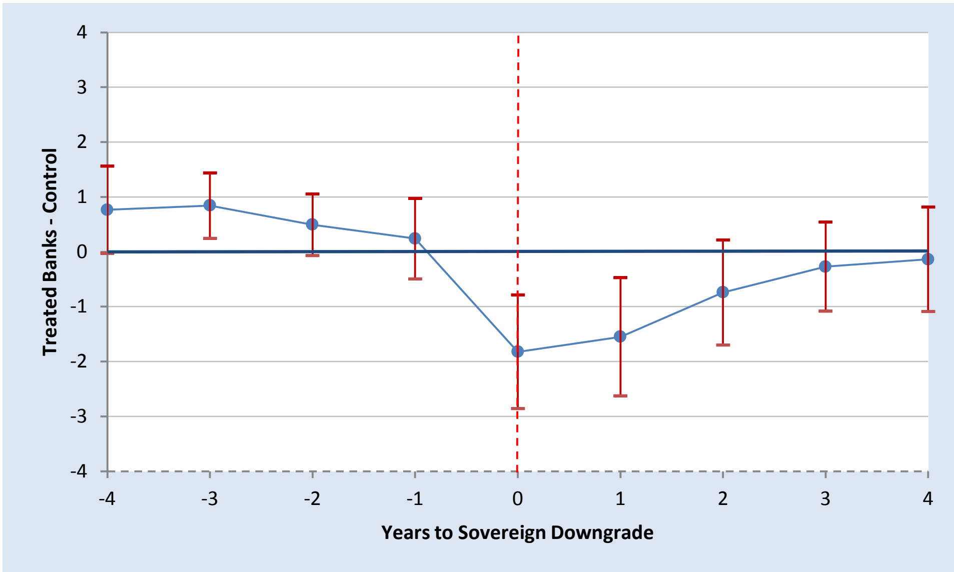
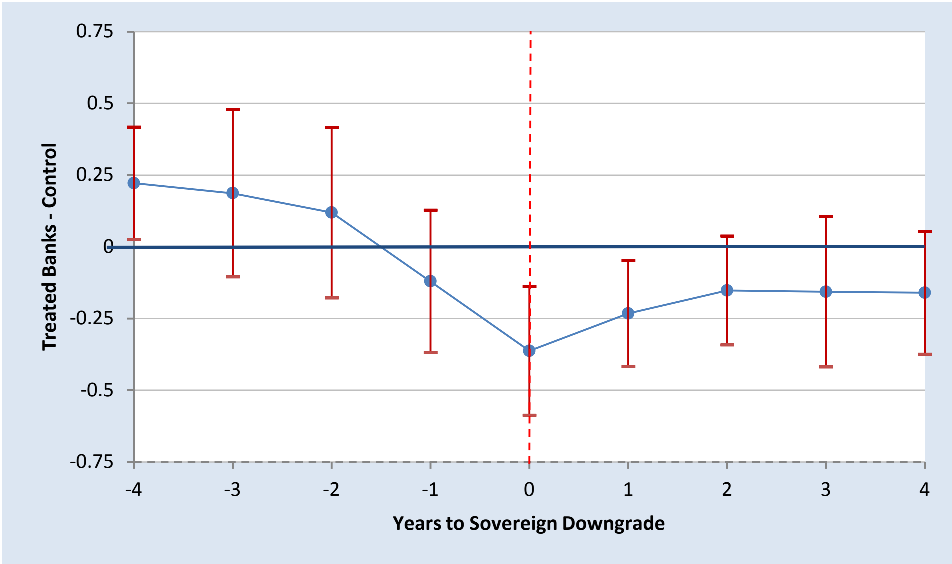


Figure 2 – Bank Lending and Sovereign Downgrade

This figure shows point estimates and 95 percent confidence intervals for the effect over time of a sovereign downgrade on the number of loans made by banks that have a rating equal to or above the sovereign ("treated" banks) relative to other banks rated lower. The dependent variable is the logarithm of the number of loans. Controls are those from Table 3. Standard errors are clustered at the country level.

Panel A – All Loans



Panel B – Loans to Foreign Borrowers

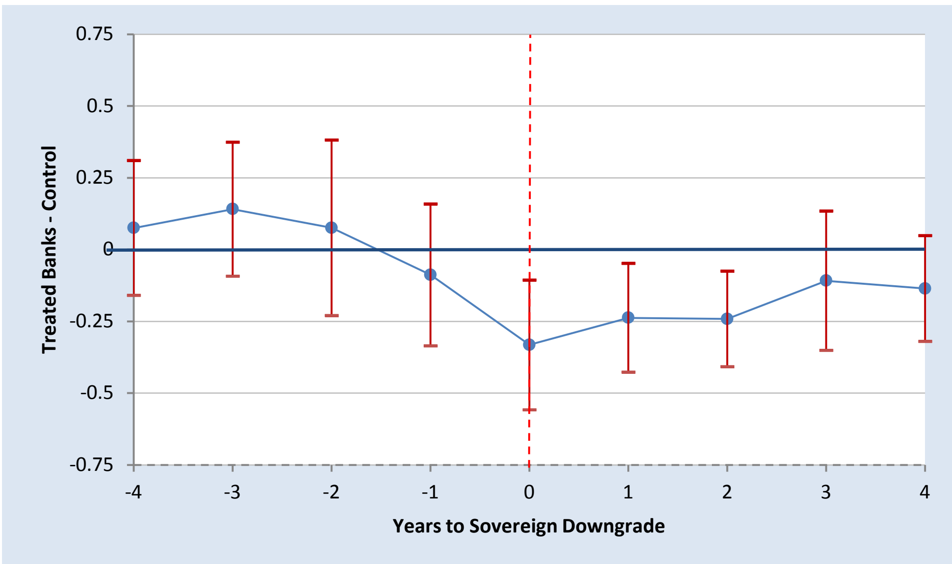


Table 1 – Summary Statistics

This table shows the mean, median, standard deviation, minimum, maximum and number of observations of variables at the lender-quarter level, except the last two in each panel (Loan Amount and Loan Spread), which are at the loan level.

Panel A – All Observations

	Mean	Median	Standard Deviation	Minimum	Maximum	Number of Observations
Lender-Quarter Level Variables						
Lender Rating	16.6	17.0	3.0	1.0	22.0	16,329
Lender Rating >= Sov. Rating (dummy)	0.20	0.00	0.40	0.00	1.00	16,329
Sovereign Downgrade (dummy)	0.02	0.00	0.15	0.00	1.00	16,329
Total Number of Loans ($ million)	51.1	10.0	105.8	0.0	1122.0	16,329
Number of Loans as Lead ($ million)	34.8	5.0	81.4	0.0	961.0	16,329
Amount of Loans as Lead ($ million)	2,463	100	8,146	0	174,000	16,329
Foreign Total Number of Loans ($ million)	27.2	2.0	64.3	0.0	597.0	16,329
Foreign Number of Loans as Lead ($ million)	19.2	1.0	46.9	0.0	442.0	16,329
Foreign Amount of Loans as Lead ($ million)	1,317	16	4,265	0	56,740	16,329
Growth Total Number of Loans (%)	0.17	0.00	0.91	-1.00	2.67	12,769
Growth Number of Loans as Lead (%)	0.12	-0.01	0.93	-1.00	2.60	11,441
Growth of Loans as Lead (%)	0.50	-0.06	1.81	-1.00	6.35	11,439
Size ($ billion)	206.1	61.9	385.3	0.1	3065.1	16,329
Profitability (%)	0.01	0.01	0.01	-0.05	0.05	16,314
Capital (%)	0.08	0.07	0.07	0.01	0.57	16,329
Liquidity (%)	0.19	0.15	0.15	0.01	0.82	16,327
Deposits (%)	0.66	0.72	0.21	0.06	0.95	16,323
Too Big Too Fail (dummy)	0.43	0.00	0.50	0.00	1.00	15,573
Government Owned (dummy)	0.11	0.00	0.32	0.00	1.00	16,329
Government Bondholdings	0.01	0.00	0.04	0.00	0.38	16,329
Loan-Level Variables						
Loan Amount ($ million)	509	156	1,234	0	50,000	930,581
Loan Spread (basis points)	180.3	150.0	134.8	15.0	687.5	656,527

Panel B – Observations with Bank Rating at the Sovereign Bound

	Mean	Median	Standard Deviation	Minimum	Maximum	Number of Observations
Lender-Quarter Level Variables						
Lender Rating	16.8	17.0	4.7	1.0	22.0	3,311
Sovereign Downgrade (dummy)	0.03	0.00	0.17	0.00	1.00	3,311
Total Number of Loans ($ million)	17.9	3.0	48.5	0.0	470.0	3,311
Number of Loans as Lead ($ million)	13.2	2.0	36.5	0.0	385.0	3,311
Amount of Loans as Lead ($ million)	714	33	2,383	0	30,410	3,311
Foreign Total Number of Loans ($ million)	12.1	1.0	36.1	0.0	467.0	3,311
Foreign Number of Loans as Lead ($ million)	8.7	1.0	27.2	0.0	382.0	3,311
Foreign Amount of Loans as Lead ($ million)	475	7	1,821	0	28,400	3,311
Growth Total Number of Loans (%)	0.10	-0.07	1.01	-1.00	2.67	2,206
Growth Number of Loans as Lead (%)	0.07	-0.14	1.02	-1.00	2.60	2,013
Growth of Loans as Lead (%)	0.51	-0.23	2.01	-1.00	6.35	2,013
Size ($ billion)	130.8	53.8	212.5	0.5	1675.2	3,311
Profitability (%)	0.01	0.01	0.01	-0.05	0.05	3,309
Capital (%)	0.11	0.08	0.10	0.01	0.57	3,311
Liquidity (%)	0.20	0.17	0.15	0.01	0.82	3,310
Deposits (%)	0.54	0.63	0.28	0.06	0.95	3,308
Too Big Too Fail (dummy)	0.54	1.00	0.50	0.00	1.00	3,204
Government Owned (dummy)	0.30	0.00	0.46	0.00	1.00	3,311
Government Bondholdings	0.01	0.00	0.05	0.00	0.38	3,311
Loan-Level Variables						
Loan Amount ($ million)	374	110	975	0	48,500	450,220
Loan Spread (basis points)	196.1	175.0	135.5	15.0	687.5	324,952

Table 2 – Sovereign Downgrade and Lender Downgrade

This table shows OLS results of the effect of a sovereign downgrade on the rating of a bank that has a rating equal to or above the sovereign. The dependent variable is the S&P rating of the bank converted to a numeric scale (where 22 represents a rating of "AAA", 21 an "AA+", and so on until 1 for a "D" rating; 0 represents unrated banks). Sovereign downgrade is an indicator variable that is equal to 1 if the sovereign suffers a negative rating change of one or more notches along the numeric rating scale. Controls include the logarithm of total bank assets, bank ROA, bank capital defined as the ratio of total equity to total assets, bank liquidity defined as liquid assets over total assets, and deposits as a proportion of assets. Observations are at the bank-quarter level. The first two columns include sovereign country fixed effects, and the last two include bank fixed effects. Columns 2 and 4 include time-varying country controls that include the ratio of government debt to GDP, the growth rate of GDP, inflation, the ratio of the total credit in the economy to GDP, and indicator variables for whether the country is experiencing a currency crisis, an inflation crisis, a sovereign domestic debt crisis, a sovereign external debt crisis, a banking crisis or a recession. For the source of all country macro controls, please see the data section. All regressions include quarter fixed effects. Standard errors are clustered at the country level. *, **, *** denote statistical significance at the 10, 5, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Lender Rating >= Sovereign Rating	2.99***	2.66***	0.79**	0.80**
	(0.32)	(0.32)	(0.35)	(0.33)
Sovereign Downgrade	-0.91***	-0.53**	-0.89***	-0.62***
	(0.33)	(0.26)	(0.24)	(0.22)
Lender Rating >= Sov. Rating x Sov. Downgrade	-1.49**	-1.36***	-1.15**	-0.94***
	(0.59)	(0.42)	(0.46)	(0.36)
Size		0.47***		0.87***
		(0.10)		(0.19)
Profitability		26.11**		28.36***
		(12.11)		(6.74)
Capital		4.33***		3.30
		(1.53)		(2.38)
Liquidity		0.44		-0.56
		(0.89)		(0.64)
Deposits		-0.55		0.98**
		(0.62)		(0.47)
Country Macro Controls		Y		Y
Country FE	Y	Y		
Quarter FE	Y	Y	Y	Y
Lender FE			Y	Y
Number of Observations	20,850	16,329	20,850	16,329
R-Squared	0.64	0.72	0.11	0.30

Table 3 – Sovereign Downgrade and Bank Lending

This table shows fixed-effects models of the effect of a sovereign downgrade on the total number of loans, the number of loans as a lead arranger, and the amount of loans as a lead arranger for banks that have a rating equal to or above the sovereign. The first six columns include all loans, and the last six only include loans in which the lender and borrower have different countries of origin. The dependent variables are all measured 2 quarters after the sovereign downgrade. Sovereign downgrade is an indicator variable that is equal to 1 if the sovereign suffers a negative rating change of one or more notches along the numeric rating scale (i.e. A to A- or A- to BBB+). Observations are at the lender-quarter level. Controls include the logarithm of total bank assets, bank ROA, bank capital defined as the ratio of total equity to total assets, bank liquidity defined as liquid assets over total assets, and deposits as a proportion of assetsAll columns include lender fixed effects. The second column for each dependent variable includes time-varying controls for the country of the lender that include the ratio of government debt to GDP, the growth rate of GDP, inflation, the ratio of the total credit in the economy to GDP, and indicator variables for whether the country is experiencing a currency crisis, an inflation crisis, a sovereign domestic debt crisis, a sovereign external debt crisis, a banking crisis or a recession. For the source of all country macro controls, please see the data section. All regressions include quarter fixed effects. Standard errors are clustered at the country level. *, **, *** denote statistical significance at the 10, 5, and 1% levels, respectively.

	All Loans						*Loans to Foreign Borrowers*					
	Total Number of Loans		Number of Loans as Lead		Amount of Loans as Lead		Total Number of Loans		Number of Loans as Lead		Amount of Loans as Lead	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Lender Rating >= Sovereign Rating	-0.06	-0.17**	-0.14	-0.17**	-0.43	-0.79	-0.09	-0.07	-0.13*	-0.06	-0.11	-0.35
	(0.09)	(0.08)	(0.09)	(0.08)	(0.46)	(0.49)	(0.08)	(0.07)	(0.08)	(0.06)	(0.47)	(0.42)
Sovereign Downgrade	-0.07	0.01	-0.13	-0.06	-1.18*	-0.57	-0.15**	-0.05	-0.17**	-0.07	-1.68***	-0.97
	(0.11)	(0.09)	(0.11)	(0.08)	(0.71)	(0.59)	(0.07)	(0.06)	(0.07)	(0.07)	(0.63)	(0.64)
Lender Rating >= Sov. Rating x Sov. Downgrade	-0.31***	-0.26*	-0.21**	-0.23**	-1.62**	-1.76*	-0.14	-0.20*	-0.11	-0.19*	-2.00***	-2.44***
	(0.12)	(0.14)	(0.09)	(0.10)	(0.77)	(0.97)	(0.09)	(0.12)	(0.09)	(0.11)	(0.71)	(0.80)
Size		0.35***		0.33***		1.39*		0.34***		0.30***		1.66***
		(0.11)		(0.12)		(0.74)		(0.09)		(0.08)		(0.60)
Profitability		1.13		0.66		5.70		3.02		3.21*		10.56
		(2.43)		(2.20)		(11.53)		(1.85)		(1.69)		(9.44)
Capital		1.99***		2.15***		11.85***		1.55**		1.26*		11.01**
		(0.69)		(0.82)		(4.06)		(0.74)		(0.65)		(4.75)
Liquidity		0.20		0.24		2.58		0.22		0.28		3.08*
		(0.28)		(0.27)		(1.61)		(0.23)		(0.21)		(1.58)
Deposits		0.41		0.35		2.41**		0.43*		0.26		1.70
		(0.27)		(0.26)		(1.10)		(0.24)		(0.22)		(1.25)
Country Macro Controls		Y		Y		Y		Y		Y		Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Number of Observations	19,877	15,502	19,877	15,502	19,877	15,502	19,877	15,502	19,877	15,502	19,877	15,502
R-Squared	0.29	0.19	0.26	0.21	0.08	0.06	0.18	0.17	0.19	0.20	0.08	0.07

Table 4 – Sovereign Downgrade and Growth of Bank Lending

This table shows OLS regressions of the effect of a sovereign downgrade on the *growth* in the total number of loans, the number of loans as a lead arranger, and the amount of loans as a lead arranger for banks that have a rating equal to or above the sovereign. The first six columns include all loans, and the last six only include loans in which the lender and borrower have different countries of origin. The dependent variables are all measured as the growth between the quarter prior to the sovereign downgrade and two quarters after that. Sovereign downgrade is an indicator variable that is equal to 1 if the sovereign suffers a negative rating change of one or more notches along the numeric rating scale (i.e. A to A- or A- to BBB+). Observations are at the lender-quarter level. Controls include the logarithm of total bank assets, bank ROA, bank capital defined as the ratio of total equity to total assets, bank liquidity defined as liquid assets over total assets, and deposits as a proportion of assets. All columns include quarter and country fixed effects. The second column for each dependent variable includes time-varying controls for the country of the lender that include the ratio of government debt to GDP, the growth rate of GDP, inflation, the ratio of the total credit in the economy to GDP, and indicator variables for whether the country is experiencing a currency crisis, an inflation crisis, a sovereign domestic debt crisis, a sovereign external debt crisis, a banking crisis or a recession. For the source of all country macro controls, please see the data section. Standard errors are clustered at the country level. *, **, *** denote statistical significance at the 10, 5, and 1% levels, respectively.

	All Loans						*Loans to Foreign Borrowers*					
	Total Number of Loans		Number of Loans as Lead		Amount of Loans as Lead		Total Number of Loans		Number of Loans as Lead		Amount of Loans as Lead	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Lender Rating >= Sovereign Rating	-0.02	0.02	-0.02	-0.02	0.00	0.00	0.02	0.04	0.00	0.02	0.07	0.07
	(0.03)	(0.04)	(0.04)	(0.04)	(0.06)	(0.08)	(0.04)	(0.05)	(0.04)	(0.05)	(0.06)	(0.07)
Sovereign Downgrade	-0.08	-0.04	-0.17**	-0.10	-0.36**	-0.22	-0.17**	-0.07	-0.30***	-0.19**	-0.35**	-0.19
	(0.06)	(0.06)	(0.07)	(0.07)	(0.16)	(0.16)	(0.07)	(0.07)	(0.10)	(0.09)	(0.16)	(0.13)
Lender Rating >= Sov. Rating x Sov. Downgrade	-0.41***	-0.35***	-0.33***	-0.30**	-0.43**	-0.36	-0.37***	-0.32***	-0.32**	-0.36***	-0.54***	-0.55***
	(0.12)	(0.11)	(0.11)	(0.12)	(0.22)	(0.23)	(0.11)	(0.10)	(0.14)	(0.13)	(0.21)	(0.19)
Size		0.01		0.06***		0.01		0.06***		0.09***		0.07***
		(0.01)		(0.01)		(0.01)		(0.01)		(0.02)		(0.03)
Profitability		-2.44		-0.23		-3.12		3.06*		5.31**		6.85*
		(1.82)		(2.19)		(3.82)		(1.77)		(2.13)		(3.64)
Capital		0.38**		0.53***		1.24***		0.16		0.29		0.74
		(0.19)		(0.20)		(0.43)		(0.49)		(0.37)		(0.55)
Liquidity		-0.03		0.13*		0.24*		0.28***		0.24*		0.34*
		(0.08)		(0.07)		(0.13)		(0.09)		(0.13)		(0.20)
Deposits		0.17**		0.01		0.00		-0.03		-0.09		-0.19*
		(0.08)		(0.06)		(0.13)		(0.07)		(0.10)		(0.11)
Country Macro Controls		Y		Y		Y		Y		Y		Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Number of Observations	15,472	12,769	13,568	11,441	13,564	11,439	11,248	9,580	9,891	8,594	9,888	8,593
R-Squared	0.10	0.11	0.11	0.12	0.06	0.06	0.15	0.17	0.16	0.18	0.08	0.09

Table 5 – Sovereign Downgrade and Bank Lending – Matched Sample

This table shows the summary statistics of the treatment and control lenders in our matched sample (Panel A), as well as the difference-in-differences and the average treatment effect on the treated banks using the Abadie-Imbens nearest-neighbor estimator of the effect of a sovereign downgrade (Panel B). The dependent variables are the total number of loans, the number of loans as a lead arranger, and the amount of loans as a lead arranger for banks that have a rating equal to or above the sovereign. The dependent variables are all measured two quarters after the downgrade. Sovereign downgrade is an indicator variable that is equal to 1 if the sovereign suffers a negative rating change of one or more notches along the numeric rating scale (i.e. A to A- or A- to BBB+). Banks are matched exactly on country and quarter, and pre-treatment covariates include logarithm of total bank assets, the bank's ROA and the bank's capital defined as the ratio of total equity to total assets. *, **, *** denote statistical significance at the 10, 5, and 1% levels, respectively.

Panel A – Summary Statistics

	Mean		Median			Kolmogorov-
	Treatment Lenders	Control Lenders	Treatment Lenders	Control Lenders	Pearson χ^2 p-value	Smirnov p-value
Log (Assets)	11.46	11.53	11.18	11.55	0.46	0.01
	(0.11)	(0.09)				
ROA (x 100)	0.70	0.30	0.66	0.37	0.00	0.00
	(0.09)	(0.04)				
Capital	0.10	0.06	0.08	0.06	0.00	0.00
	(0.01)	(0.00)				
Liquidity	0.16	0.12	0.15	0.10	0.00	0.00
	(0.01)	(0.01)				
Deposits	0.62	0.69	0.62	0.64	0.14	0.00
	(0.02)	(0.01)				

Panel B – Difference-in-Differences Estimates

	Growth in Lending around Sovereign Downgrade (%)				Number of
	Treatment Lenders	Control Lenders	Difference-in Difference	ATT	Treated Lenders
All Loans					
Total Number of Loans	-0.41***	-0.08	-0.32***	-0.27**	46
	(0.05)	(0.07)	(0.08)	(0.13)	
Number of Loans As Lead	-0.45***	-0.24***	-0.21***	-0.51***	42
	(0.05)	(0.06)	(0.07)	(0.13)	
Amount of Loans As Lead	-0.26**	0.05	-0.32**	-0.56***	42
	(0.10)	(0.11)	(0.14)	(0.21)	
Loans to Foreign Borrowers					
Total Foreign Loans	-0.38***	0.04	-0.42***	-0.52***	34
	(0.06)	(0.09)	(0.11)	(0.18)	
Foreign Loans As Lead	-0.55***	-0.19**	-0.37***	-0.32*	32
	(0.05)	(0.08)	(0.10)	(0.17)	
Foreign Amount As Lead	-0.45***	0.08	-0.53***	-0.38	32
	(0.08)	(0.13)	(0.16)	(0.26)	

Table 6 – Sovereign Downgrade, Loan Amount and Spread – Loan-Level Tests

This table shows OLS regressions of the effect of a sovereign downgrade on the size (in logarithms) and pricing of loans. Sovereign downgrade is an indicator variable that is equal to 1 if the sovereign where the lender is located suffers a negative rating change of one or more notches along the numeric rating scale (i.e. A to A- or A- to BBB+) at any point in the two quarters prior to the date of the loan. Observations are at the loan level. Lender controls include the logarithm of total bank assets, the bank's ROA, the bank's capital defined as the ratio of total equity to total assets, and indicators for whether the lender was a previous lead arranger or participant on a loan for the same borrower. Borrower controls include the borrower's total assets, Tobin's Q, leverage (measured as total financial debt over total assets), property, plant and equipment as a proportion of total assets, an indicator for whether the borrower is rated, and the borrower rating as a numeric scale. Loan controls include indicators for the loan purpose (general purpose, debt repayment, working capital, take-over, and other term loan), as well as indicators for senior loans and secured loans. For detail on the country macro controls please see the description included in the previous tables. All regressions include year fixed effects. Standard errors are clustered at the country level. *, **, *** denote statistical significance at the 10, 5, and 1% levels, respectively.

Panel A – All Loans

	Loan Amount			Loan Spread		
	(1)	(2)	(3)	(4)	(5)	(6)
Lender Rating >= Sovereign Rating	0.09**	0.05	0.05	-2.38	-1.44	-1.79
	(0.04)	(0.04)	(0.04)	(4.58)	(4.00)	(3.32)
Sovereign Downgrade	0.04	0.06**	0.05**	-2.98	-4.61	-4.47
	(0.03)	(0.03)	(0.03)	(5.26)	(3.18)	(3.24)
Lender Rating >= Sov. Rating x Sov. Downgrade	-0.24***	-0.15**	-0.13*	45.39***	20.06**	17.35**
	(0.06)	(0.07)	(0.07)	(12.65)	(8.59)	(8.59)
Lender Controls		Y	Y		Y	Y
Borrower Controls		Y	Y		Y	Y
Loan Controls			Y			Y
Country Macro Controls		Y	Y		Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Lender x Borrower FE	Y	Y	Y	Y	Y	Y
Number of Observations	930,581	368,412	368,412	657,254	279,259	279,259
R-Squared	0.88	0.88	0.88	0.84	0.85	0.86

Panel B – Loans to Foreign Borrowers

	Loan Amount			Loan Spread		
	(1)	(2)	(3)	(4)	(5)	(6)
Lender Rating >= Sovereign Rating	0.08***	0.07**	0.07**	-5.49	-3.30	-3.49
	(0.03)	(0.03)	(0.03)	(3.95)	(4.14)	(3.65)
Sovereign Downgrade	0.05	0.01	0.02	-0.21	-1.63	-1.14
	(0.03)	(0.02)	(0.02)	(2.90)	(4.51)	(4.19)
Lender Rating >= Sov. Rating x Sov. Downgrade	-0.19***	-0.12*	-0.11*	3.09	-0.80	-2.84
	(0.07)	(0.07)	(0.06)	(8.28)	(7.42)	(7.37)
Lender Controls		Y	Y		Y	Y
Borrower Controls		Y	Y		Y	Y
Loan Controls			Y			Y
Country Macro Controls		Y	Y		Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Lender x Borrower FE	Y	Y	Y	Y	Y	Y
Number of Observations	480,361	199,119	199,119	332,041	149,303	149,303
R-Squared	0.83	0.83	0.84	0.85	0.86	0.88

Table 7 – Sovereign Downgrade and Bank Lending –Lender-Borrower-Quarter Logit Model

This table shows logit regressions with lender-borrower fixed effects of the effect of a sovereign downgrade on the probability of observing a loan by a given lender to a borrower in each quarter. Sovereign downgrade is an indicator variable that is equal to 1 if the sovereign where the lender is located suffers a negative rating change of one or more notches along the numeric rating scale (i.e. A to A- or A- to BBB+) relative to the previous quarter. Observations are at the lender-borrower-quarter level. Lender controls include the logarithm of total bank assets, the bank's ROA, the bank's capital defined as the ratio of total equity to total assets, and indicators for whether the lender was a previous lead arranger or participant on a loan for the same borrower. Borrower controls include the borrower's total assets, Tobin's Q, leverage (measured as total financial debt over total assets), property, plant and equipment as a proportion of total assets, an indicator for whether the borrower is rated, and the borrower rating as a numeric scale. All regressions include quarter fixed effects. Standard errors are clustered at the country level. *, **, *** denote statistical significance at the 10, 5, and 1% levels, respectively.

Panel A – All Loans

	Total Number of Loans		Number of Loans as Lead	
	(1)	(2)	(3)	(4)
Lender Rating >= Sovereign Rating	0.03	-0.01	0.04*	-0.01
	(0.02)	(0.03)	(0.02)	(0.03)
Sovereign Downgrade	0.01	-0.05*	0.02	-0.05
	(0.02)	(0.03)	(0.02)	(0.03)
Lender Rating >= Sov. Rating x Sov. Downgrade	-0.24***	-0.23**	-0.25***	-0.28**
	(0.07)	(0.10)	(0.07)	(0.11)
Lender Controls		Y		Y
Borrower Controls		Y		Y
Country Macro Controls		Y		Y
Quarter FE	Y	Y	Y	Y
Lender x Borrower FE	Y	Y	Y	Y
Number of Observations	2,530,825	1,308,022	2,440,768	1,249,050
R-Squared	0.03	0.04	0.03	0.04

Panel B –Loans to Foreign Borrowers

	Total Number of Loans		Number of Loans as Lead	
	(1)	(2)	(3)	(4)
Lender Rating >= Sovereign Rating	-0.01	0.03	0.01	0.05
	(0.02)	(0.03)	(0.03)	(0.04)
Sovereign Downgrade	-0.07**	-0.08*	-0.05	-0.06
	(0.03)	(0.04)	(0.04)	(0.05)
Lender Rating >= Sov. Rating x Sov. Downgrade	-0.31***	-0.21*	-0.33***	-0.25*
	(0.09)	(0.12)	(0.10)	(0.13)
Lender Controls		Y		Y
Borrower Controls		Y		Y
Country Macro Controls		Y		Y
Quarter FE	Y	Y	Y	Y
Lender x Borrower FE	Y	Y	Y	Y
Number of Observations	1,301,937	703,414	1,249,009	669,496
R-Squared	0.04	0.05	0.04	0.05

Table 8 – Sample Excluding Banks Too Big to Fail and High Creditor Rights Countries

This table shows OLS regressions of the effect of a sovereign downgrade on the total number of loans, the number of loans as a lead arranger, and the amount of loans as a lead arranger for banks that have a rating equal to or above the sovereign for two subsamples: Panel A considers only banks that are below the "too big to fail" threshold, defined as a ratio of bank liabilities to GDP above the 75th percentile of the distribution in the sample (10% of GDP); Panel B includes only countries with above-median country-level creditor rights taken form Djankov, McLiesh, and Shleifer (2007). Bank and country controls are otherwise the same as in Table 3 and Table 4 The first three columns in each panel use a fixed effects model like the one in Table 3, and the last three columns use growth rates as the dependent variable (as in Table 4). Observations are at the lender-quarter level. All columns include quarter and country fixed effects. Standard errors are clustered at the country level. *, **, *** denote statistical significance at the 10, 5, and 1% levels, respectively.

Panel A – Sample Excluding Banks Too Big to Fail

	Level			*Growth*		
	Total Number of Loans	Number of Loans as Lead	Amount of Loans as Lead	Total Number of Loans	Number of Loans as Lead	Amount of Loans as Lead
	(1)	(2)	(3)	(4)	(5)	(6)
Lender Rating >= Sovereign Rating	-0.24**	-0.23**	-1.96***	0.03	-0.07	0.10
	(0.09)	(0.11)	(0.72)	(0.07)	(0.08)	(0.12)
Sovereign Downgrade	0.15**	0.03	0.19	-0.04	0.01	-0.12
	(0.06)	(0.06)	(0.71)	(0.10)	(0.08)	(0.16)
Lender Rating >= Sov. Rating x Sov. Downgrade	-0.35*	-0.29**	-2.39	-0.56***	-0.46**	-0.29
	(0.20)	(0.15)	(1.64)	(0.20)	(0.22)	(0.56)
Lender Controls	Y	Y	Y	Y	Y	Y
Country Macro Controls	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y			
Number of Observations	8,439	8,439	8,439	6,555	5,456	5,455
R-Squared	0.16	0.14	0.05	0.08	0.08	0.05

Panel B – High Creditor Rights Countries

	Level			*Growth*		
	Total Number of Loans	Number of Loans as Lead	Amount of Loans as Lead	Total Numbre of Loans	Number of Loans as Lead	Amount of Loans as Lead
	(1)	(2)	(3)	(4)	(5)	(6)
Lender Rating >= Sovereign Rating	-0.18*	-0.19*	-0.90	0.04	0.00	-0.03
	(0.10)	(0.10)	(0.63)	(0.03)	(0.03)	(0.08)
Sovereign Downgrade	0.10	0.00	0.18	0.09	0.04	0.06
	(0.08)	(0.06)	(0.50)	(0.08)	(0.07)	(0.12)
Lender Rating >= Sov. Rating x Sov. Downgrade	-0.31*	-0.29***	-2.25**	-0.48***	-0.46***	-0.62**
	(0.19)	(0.11)	(1.08)	(0.12)	(0.13)	(0.28)
Lender Controls	Y	Y	Y	Y	Y	Y
Country Macro Controls	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y			
Number of Observations	9,452	9,452	9,452	7,569	6,925	6,923
R-Squared	0.20	0.23	0.07	0.09	0.12	0.06

Table 9 – Placebo Test – Banking Crises without Sovereign Downgrade

This table shows a OLS models of the effect of a banking crisis *without a sovereign downgrade* on the total number of loans, the number of loans as a lead arranger, and the amount of loans as a lead arranger for banks that have a rating equal to or above the sovereign. The first three columns in each panel use all loans, and the last three columns consider only loans to foreign borrowers. Treatment is defined as a banking crisis (per the Reinhart Rogoff (2009) definition, extended to 2012) without a contemporaneous sovereign downgrade, or one in the three previous quarters. The first three columns in each panel use a fixed effects model like the one in Table 3, and the last three columns use growth rates as the dependent variable (as in Table 4). Observations are at the lender-quarter level. All regressions include the same controls as those in Table 3 and Table 4. Standard errors are clustered at the country level. *, **, *** denote statistical significance at the 10, 5, and 1% levels, respectively.

Panel A – All Loans

	Level			*Growth*		
	Total Number of Loans	Number of Loans as Lead	Amount of Loans as Lead	Total Number of Loans	Number of Loans as Lead	Amount of Loans as Lead
	(1)	(2)	(3)	(4)	(5)	(6)
Lender Rating >= Sovereign Rating	-0.21**	-0.20**	-0.93*	-0.03	-0.04	-0.17
	(0.09)	(0.08)	(0.48)	(0.04)	(0.04)	(0.14)
Banking Crisis	-0.17	-0.06	0.71	0.13	0.27***	0.14
	(0.16)	(0.13)	(0.79)	(0.18)	(0.10)	(0.27)
Lender Rating >= Sov. Rating x Banking Crisis	0.35***	0.28***	1.08	-0.07	-0.08	0.10
	(0.11)	(0.09)	(0.94)	(0.09)	(0.08)	(0.16)
Lender Controls	Y	Y	Y	Y	Y	Y
Country Macro Controls	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y			
Number of Observations	15,502	15,502	15,502	7,569	6,925	6,923
R-Squared	0.20	0.21	0.06	0.08	0.10	0.05

Panel B – Loans to Foreign Borrowers

	Level			*Growth*		
	Total Number of Loans	Number of Loans as Lead	Amount of Loans as Lead	Total Number of Loans	Number of Loans as Lead	Amount of Loans as Lead
	(1)	(2)	(3)	(4)	(5)	(6)
Lender Rating >= Sovereign Rating	-0.09	-0.08	-0.42	-0.03	-0.02	-0.12
	(0.07)	(0.06)	(0.43)	(0.04)	(0.05)	(0.11)
Banking Crisis	-0.05	-0.06	0.69	0.11	0.16	-0.19
	(0.10)	(0.10)	(0.80)	(0.10)	(0.12)	(0.26)
Lender Rating >= Sov. Rating x Banking Crisis	0.09	0.13	0.01	-0.14	-0.15	-0.03
	(0.11)	(0.10)	(0.88)	(0.10)	(0.10)	(0.16)
Lender Controls	Y	Y	Y	Y	Y	Y
Country Macro Controls	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y			
Number of Observations	15,502	15,502	15,502	6,058	5,548	5,547
R-Squared	0.17	0.20	0.07	0.15	0.16	0.07

Internet Appendix to
"Does Sovereign Credit Risk Affect Bank Lending? Evidence from Sovereign Rating Downgrades"

Table A1 –S&P Credit Ratings Conversion to a Numerical Scale

Numerical Rating	Rating Notation
22	AAA
21	AA+
20	AA
19	AA-
18	A+
17	A
16	A-
15	BBB+
14	BBB
13	BBB-
12	BB+
11	BB
10	BB-
9	B+
8	B
7	B-
6	CCC+
5	CCC
4	CCC-
3	CC
2	C
1	SD/D

Table A2 – Sovereign Downgrades in the Sample of Banks at the Sovereign Bound

This table shows the number of banks by country and year where the bank has a rating equal to or above the sovereign, and where the sovereign suffers a downgrade. So, for example, in 2000 Argentina suffered a rating downgrade, and there were 2 Argentinian banks that had a rating equal or higher than the sovereign as of the quarter before the sovereign downgrade.

	1989	1997	1998	1999	2000	2001	2002	2003	2005	2006	2008	2009	2010	2011	2012	Total
Argentina					2	8									1	11
Australia	1															1
Brazil				1			3									4
China				2												2
Egypt							2							6	7	15
Spain														2	5	7
France															2	2
Greece													1	5	4	10
Hungary											1	1		1	1	4
Indonesia			1		1	2	2									6
India			1													1
Italy										1				4	5	10
Japan						3	3							1		7
Korea, Republic o		2														2
Lebanon					1	1	1				1					4
Malaysia		1	1													2
Panama						2										2
Philippines								1	1							2
Portugal												1	1	3		5
Russian Federation											2					2
Thailand			1													1
Turkey						5										5
United States														1		1
Venezuela				1			1									2
South Africa															2	2
Total	1	3	4	4	4	21	12	1	1	1	4	2	2	23	27	110

Table A3 – Sovereign Downgrade and Lender Downgrade – Logit Model

This table reports the effect of a sovereign downgrade on the probability of a downgrade for a bank that has a rating equal to or above the sovereign. Downgrades (for banks and sovereigns) are indicator variables that are equal to 1 for a negative rating change of one or more notches along the numeric rating scale. Controls include the logarithm of total bank assets, bank ROA, bank capital defined as the ratio of total equity to total assets, bank liquidity defined as liquid assets over total assets, and deposits as a proportion of assetsThe first two columns include sovereign country fixed effects, and the last two include bank fixed effects. Columns 2 and 4 include time-varying country controls that include the ratio of government debt to GDP, the growth rate of GDP, inflation, the ratio of the total credit in the economy to GDP, and indicator variables for whether the country is experiencing a currency crisis, an inflation crisis, a sovereign domestic debt crisis, a sovereign external debt crisis, a banking crisis or a recession. For the source of all country macro controls, please see the data section. All regressions include quarter fixed effects. Standard errors are clustered at the country level. *, **, *** denote statistical significance at the 10, 5, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Lender Rating >= Sovereign Rating	-0.56***	-0.79***	0.23	0.60**
	(0.21)	(0.28)	(0.21)	(0.25)
Sovereign Downgrade	2.84***	2.10***	2.45***	1.94***
	(0.34)	(0.35)	(0.15)	(0.18)
Lender Rating >= Sov. Rating x Sov. Downgrac	4.01***	5.68***	2.93***	3.78***
	(0.78)	(1.17)	(0.37)	(0.55)
Size		0.20***		0.44***
		(0.05)		(0.15)
Profitability		-35.17***		-28.93***
		(8.78)		(5.86)
Capital		-1.16		1.07
		(1.93)		(3.26)
Liquidity		-0.55		-0.41
		(0.40)		(0.79)
Deposits		-0.60		1.06
		(0.42)		(0.76)
Country Macro Controls		Y		Y
Country FE	Y	Y		
Quarter FE	Y	Y	Y	Y
Lender FE			Y	Y
Number of Observations	17,372	12,962	15,219	11,545
R-Squared	0.25	0.37	0.14	0.29

Table A4 – Sovereign Downgrade and Growth of Bank Lending - Lender Fixed Effects

This table shows fixed effects models of the effect of a sovereign downgrade on the *growth* in the total number of loans, the number of loans as a lead arranger, and the amount of loans as a lead arranger for banks that have a rating equal to or above the sovereign. The first six columns include all loans, and the last six only include loans in which the lender and borrower have different countries of origin. All regressions include lender fixed effects. The dependent variables are all measured as the growth between the quarter prior to the sovereign downgrade and two quarters after that. Sovereign downgrade is an indicator variable that is equal to 1 if the sovereign suffers a negative rating change of one or more notches along the numeric rating scale. Controls include the logarithm of total bank assets, bank ROA, bank capital defined as the ratio of total equity to total assets, bank liquidity defined as liquid assets over total assets, and deposits as a proportion of assetsAll columns include quarter and lender fixed effects. Observations are at the lender-quarter level. The second column for each dependent variable includes time-varying controls for the country of the lender that include the ratio of government debt to GDP, the growth rate of GDP, inflation, the ratio of the total credit in the economy to GDP, and indicator variables for whether the country is experiencing a currency crisis, an inflation crisis, a sovereign domestic debt crisis, a sovereign external debt crisis, a banking crisis or a recession. For the source of all country macro controls, please see the data section. Standard errors are clustered at the country level. *, **, *** denote statistical significance at the 10, 5, and 1% levels, respectively.

	All Loans						*Loans to Foreign Borrowers*					
	Total Number of Loans		Number of Loans as Lead		Amount of Loans as Lead		Total Number of Loans		Number of Loans as Lead		Amount of Loans as Lead	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Lender Rating >= Sovereign Rating	-0.01	-0.03	-0.02	-0.05	-0.07	-0.10	0.02	-0.03	0.00	-0.04	-0.04	-0.10
	(0.05)	(0.04)	(0.04)	(0.04)	(0.11)	(0.11)	(0.04)	(0.04)	(0.04)	(0.04)	(0.08)	(0.09)
Sovereign Downgrade	-0.07	-0.04	-0.16**	-0.11	-0.37**	-0.25	-0.15**	-0.09	-0.25***	-0.17*	-0.32**	-0.19
	(0.07)	(0.07)	(0.07)	(0.07)	(0.16)	(0.16)	(0.07)	(0.08)	(0.07)	(0.09)	(0.15)	(0.14)
Lender Rating >= Sov. Rating x Sov. Downgrade	-0.44***	-0.35***	-0.39***	-0.34***	-0.44**	-0.36*	-0.44***	-0.35***	-0.46***	-0.43***	-0.66***	-0.60**
	(0.10)	(0.10)	(0.10)	(0.12)	(0.22)	(0.21)	(0.10)	(0.10)	(0.12)	(0.14)	(0.24)	(0.24)
Size		-0.02		0.03		0.02		-0.01		0.02		0.06
		(0.03)		(0.05)		(0.10)		(0.03)		(0.04)		(0.08)
Profitability		-3.17		-1.31		-5.02		3.48**		6.51***		8.00**
		(2.23)		(2.66)		(4.26)		(1.56)		(2.27)		(3.94)
Capital		0.55		0.89		1.81		0.16		-0.28		0.69
		(0.35)		(0.56)		(1.14)		(0.55)		(0.64)		(1.04)
Liquidity		0.13		0.06		0.43		0.37**		0.42**		0.89***
		(0.12)		(0.17)		(0.30)		(0.15)		(0.19)		(0.32)
Deposits		0.24***		0.21**		0.39*		0.07		-0.05		-0.03
		(0.07)		(0.09)		(0.22)		(0.09)		(0.14)		(0.21)
Country Macro Controls		Y		Y		Y		Y		Y		Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Number of Observations	15,472	12,769	13,568	11,441	13,564	11,439	11,248	9,580	9,891	8,594	9,888	8,593
R-Squared	0.10	0.10	0.10	0.11	0.05	0.05	0.14	0.15	0.14	0.15	0.07	0.08

Table A5 – Sovereign Downgrade, Loan Amount and Spread – Loan-Level Tests Excluding Financials and Public Administration

This table shows OLS regressions of the effect of a sovereign downgrade on the size (in logarithms) and pricing of loans excluding the sample of borrowers that are in the financial sector (SIC codes beginning with 6) or that are part of the public administration (SIC codes beginning with 9). Sovereign downgrade is an indicator variable that is equal to 1 if the sovereign where the lender is located suffers a negative rating change of one or more notches along the numeric rating scale (i.e. A to A- or A- to BBB+) at any point in the two quarters prior to the date of the loan. Observations are at the loan level. Lender controls include the logarithm of total bank assets, the bank's ROA, the bank's capital defined as the ratio of total equity to total assets, and indicators for whether the lender was a previous lead arranger or participant on a loan for the same borrower. Borrower controls include the borrower's total assets, Tobin's Q, leverage (measured as total financial debt over total assets), property, plant and equipment as a proportion of total assets, an indicator for whether the borrower is rated, and the borrower rating as a numeric scale. Loan controls include indicators for the loan purpose (general purpose, debt repayment, working capital, take-over, and other term loan), as well as indicators for senior loans and secured loans. For detail on the country macro controls please see the description included in the previous tables. All regressions include year fixed effects. Standard errors are clustered at the country level. *, **, *** denote statistical significance at the 10, 5, and 1% levels, respectively.

	Loan Amount			Loan Spread		
	(1)	(2)	(3)	(4)	(5)	(6)
Lender Rating >= Sovereign Rating	0.08**	0.04	0.05	-0.40	-0.84	-1.15
	(0.04)	(0.04)	(0.04)	(5.44)	(4.42)	(3.66)
Sovereign Downgrade	0.03	0.05	0.04	-3.11	-6.84**	-6.48**
	(0.03)	(0.03)	(0.03)	(5.22)	(3.11)	(3.13)
Lender Rating >= Sov. Rating x Sov. Downgrade	-0.26***	-0.18**	-0.15**	46.72***	24.11**	21.70**
	(0.07)	(0.07)	(0.07)	(13.31)	(10.06)	(10.37)
Lender Controls		Y	Y		Y	Y
Borrower Controls		Y	Y		Y	Y
Loan Controls			Y			Y
Country Macro Controls		Y	Y		Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Lender x Borrower FE	Y	Y	Y	Y	Y	Y
Number of Observations	747,752	311,341	311,341	544,051	243,160	243,160
R-Squared	0.89	0.89	0.89	0.83	0.84	0.86

Table A6 – Sample Excluding to Banks Too Big to Fail and High Creditor Rights Countries – Foreign Borrowers

This table shows OLS regressions of the effect of a sovereign downgrade on the total number of loans, the number of loans as a lead arranger, and the amount of loans as a lead arranger for banks that have a rating equal to or above the sovereign for two subsamples: Panel A considers only banks that are below the "too big to fail" threshold, defined as a ratio of bank liabilities to GDP above the 75th percentile of the distribution in the sample (10% of GDP); Panel B includes only countries with above-median country-level creditor rights taken from Djankov, McLiesh and Shleifer (2007) definition. Bank and country controls are otherwise the same as in Table 3 and Table 4 The first three columns in each panel use a fixed effects model like the one in Table 3, and the last three columns use growth rates as the dependent variable (as in Table 4). Observations are at the lender-quarter level. All columns include quarter and country fixed effects. Standard errors are clustered at the country level. *, **, *** denote statistical significance at the 10, 5, and 1% levels, respectively.

Panel A – Sample Excluding Banks Too Big to Fail

	Level			*Growth*		
	Total Number of Loans	Number of Loans as Lead	Amount of Loans as Lead	Total Number of Loans	Number of Loans as Lead	Amount of Loans as Lead
	(1)	(2)	(3)	(4)	(5)	(6)
Lender Rating >= Sovereign Rating	-0.11	-0.09	-1.33	0.06	-0.01	0.17*
	(0.11)	(0.09)	(0.82)	(0.06)	(0.08)	(0.09)
Sovereign Downgrade	0.03	0.00	0.16	0.05	-0.02	0.07
	(0.07)	(0.06)	(0.72)	(0.16)	(0.15)	(0.30)
Lender Rating >= Sov. Rating x Sov. Downgrade	-0.21*	-0.19	-2.47*	-0.49**	-0.55**	-0.55
	(0.11)	(0.12)	(1.32)	(0.21)	(0.22)	(0.52)
Lender Controls	Y	Y	Y	Y	Y	Y
Country Macro Controls	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y			
Number of Observations	8,439	8,439	8,439	3,807	3,112	3,111
R-Squared	0.10	0.10	0.05	0.14	0.15	0.08

Panel B – High Creditor Rights Countries

	Level			*Growth*		
	Total Number of Loans	Number of Loans as Lead	Amount of Loans as Lead	Total Number of Loans	Number of Loans as Lead	Amount of Loans as Lead
	(1)	(2)	(3)	(4)	(5)	(6)
Lender Rating >= Sovereign Rating	-0.08	-0.07	-0.38	0.03	0.01	0.08
	(0.09)	(0.08)	(0.58)	(0.05)	(0.05)	(0.06)
Sovereign Downgrade	0.04	0.01	-0.11	-0.01	-0.17	-0.04
	(0.06)	(0.05)	(0.43)	(0.10)	(0.15)	(0.19)
Lender Rating >= Sov. Rating x Sov. Downgrade	-0.25*	-0.27**	-3.08***	-0.41***	-0.32	-0.53**
	(0.15)	(0.12)	(0.90)	(0.12)	(0.19)	(0.26)
Lender Controls	Y	Y	Y	Y	Y	Y
Country Macro Controls	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y			
Number of Observations	9,452	9,452	9,452	6,058	5,548	5,547
R-Squared	0.18	0.21	0.08	0.16	0.18	0.09

Table A7 – Banks Too Big to Fail and Creditor Rights Controls

This table shows OLS regressions of the effect of a sovereign downgrade on the total number of loans, the number of loans as a lead arranger, and the amount of loans as a lead arranger for banks that have a rating equal to or above the sovereign. This table includes additional controls for whether a bank is "too big to fail," defined as a ratio of bank liabilities to GDP above the 75th percentile of the distribution in the sample (10% of GDP), as well as for country-level creditor rights rights using the La Porta, Lopez-de-Silanes, Shleifer, and Vishny (1998) and Djankov, McLiesh and Shleifer (2007) definition and an indicator for banks that are government owned. Bank and country controls are otherwise the same as in Table 3 and Table 4. The first three columns in each panel use a fixed effects model like the one in Table 3, and the last three columns use growth rates as the dependent variable (as in Table 4). All columns include quarter and country fixed effects. Standard errors are clustered at the country level. *, **, *** denote statistical significance at the 10, 5, and 1% levels, respectively.

Panel A – All Loans

	Level			*Growth*		
	Total Number of Loans	Number of Loans as Lead	Amount of Loans as Lead	Total Number of Loans	Number of Loans as Lead	Amount of Loans as Lead
	(1)	(2)	(3)	(4)	(5)	(6)
Lender Rating >= Sovereign Rating	-0.22***	-0.21***	-0.98**	0.03	-0.02	0.01
	(0.07)	(0.08)	(0.49)	(0.04)	(0.05)	(0.08)
Sovereign Downgrade	0.03	-0.04	-0.52	-0.07	-0.09	-0.24
	(0.09)	(0.08)	(0.61)	(0.07)	(0.07)	(0.17)
Lender Rating >= Sov. Rating x Sov. Downgrade	-0.26*	-0.23**	-1.58	-0.31***	-0.29**	-0.35
	(0.14)	(0.10)	(0.98)	(0.11)	(0.13)	(0.24)
Too Big Too Fail	-0.13	-0.12	-1.09*	0.02	-0.03	-0.07
	(0.10)	(0.11)	(0.59)	(0.04)	(0.03)	(0.08)
Government Owned				-0.02	0.03	0.11
				(0.04)	(0.05)	(0.10)
High Creditor Rights	-0.45***	-0.36**	-4.36***	-0.08	-0.01	-0.07
	(0.16)	(0.18)	(0.68)	(0.08)	(0.09)	(0.19)
Lender Controls	Y	Y	Y	Y	Y	Y
Country Macro Controls	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y			
Number of Observations	14,527	14,527	14,527	11,875	10,577	10,575
R-Squared	0.20	0.22	0.06	0.11	0.12	0.06

Panel B – Loans to Foreign Borrowers

	Level			*Growth*		
	Total Number of Loans	Number of Loans as Lead	Amount of Loans as Lead	Total Number of Loans	Number of Loans as Lead	Amount of Loans as Lead
	(1)	(2)	(3)	(4)	(5)	(6)
Lender Rating >= Sovereign Rating	-0.11	-0.09	-0.52	0.01	-0.01	0.04
	(0.07)	(0.06)	(0.43)	(0.05)	(0.05)	(0.07)
Sovereign Downgrade	-0.02	-0.05	-0.83	-0.07	-0.16*	-0.14
	(0.06)	(0.07)	(0.67)	(0.07)	(0.09)	(0.13)
Lender Rating >= Sov. Rating x Sov. Downgrade	-0.20*	-0.20*	-2.37***	-0.30***	-0.37***	-0.57***
	(0.12)	(0.11)	(0.82)	(0.11)	(0.14)	(0.20)
Too Big Too Fail	-0.09	-0.05	-0.72	0.01	0.01	0.01
	(0.08)	(0.09)	(0.48)	(0.05)	(0.06)	(0.07)
Government Owned				0.06	0.03	0.10
				(0.04)	(0.05)	(0.07)
High Creditor Rights	-0.69***	-0.53***	-5.62***	-0.26***	-0.29***	-0.73***
	(0.15)	(0.16)	(0.92)	(0.08)	(0.09)	(0.15)
Lender Controls	Y	Y	Y	Y	Y	Y
Country Macro Controls	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y			
Number of Observations	14,527	14,527	14,527	8,753	7,797	7,796
R-Squared	0.18	0.21	0.07	0.17	0.18	0.10

Table A8 – Government Bond Holdings Controls from Bankscope

This table shows OLS regressions of the effect of a sovereign downgrade on the total number of loans, the number of loans as a lead arranger, and the amount of loans as a lead arranger for banks that have a rating equal to or above the sovereign. This table includes additional controls for the holdings of government bonds from Bankscope. Missing observations are replaced with zero, and we include an indicator variable for missing observations. Bank and country controls are otherwise the same as in Table 3 and Table 4. Observations are at the lender-quarter level. Panel A includes all borrowers, and Panel B uses only loans to foreign borrowers. The first three columns in each panel use a fixed effects model like the one in Table 3, and the last three columns use growth rates as the dependent variable (as in Table 4). All columns include quarter and country fixed effects. Standard errors are clustered at the country level. *, **, *** denote statistical significance at the 10, 5, and 1% levels, respectively.

Panel A – All Loans

	Level			*Growth*		
	Total Number of Loans	Number of Loans as Lead	Amount of Loans as Lead	Total Number of Loans	Number of Loans as Lead	Amount of Loans as Lead
	(1)	(2)	(3)	(4)	(5)	(6)
Lender Rating >= Sovereign Rating	-0.17**	-0.18**	-0.82*	0.03	-0.02	0.01
	(0.09)	(0.08)	(0.50)	(0.04)	(0.04)	(0.08)
Sovereign Downgrade	0.01	-0.06	-0.60	-0.04	-0.10	-0.24
	(0.09)	(0.08)	(0.59)	(0.07)	(0.07)	(0.16)
Lender Rating >= Sov. Rating x Sov. Downgrade	-0.25*	-0.21**	-1.70*	-0.34***	-0.30**	-0.35
	(0.13)	(0.09)	(0.95)	(0.11)	(0.12)	(0.22)
Government Bondholdings	0.20	0.25	2.39	0.46	0.40	0.43
	(0.42)	(0.51)	(3.31)	(0.37)	(0.44)	(0.79)
Lender Controls	Y	Y	Y	Y	Y	Y
Country Macro Controls	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y			
Number of Observations	15,502	15,502	15,502	12,769	11,441	11,439
R-Squared	0.19	0.21	0.06	0.11	0.12	0.07

Panel B – Loans to Foreign Borrowers

	Level			*Growth*		
	Total Number of Loans	Number of Loans as Lead	Amount of Loans as Lead	Total Number of Loans	Number of Loans as Lead	Amount of Loans as Lead
	(1)	(2)	(3)	(4)	(5)	(6)
Lender Rating >= Sovereign Rating	-0.07	-0.07	-0.38	0.04	0.02	0.07
	(0.07)	(0.06)	(0.43)	(0.05)	(0.05)	(0.07)
Sovereign Downgrade	-0.05	-0.08	-1.00	-0.07	-0.19**	-0.19
	(0.07)	(0.07)	(0.65)	(0.07)	(0.09)	(0.13)
Lender Rating >= Sov. Rating x Sov. Downgrade	-0.19	-0.18*	-2.38***	-0.33***	-0.37***	-0.55***
	(0.12)	(0.11)	(0.80)	(0.10)	(0.13)	(0.20)
Government Bondholdings	0.64	0.45	3.44	0.31	0.54	0.25
	(0.42)	(0.44)	(2.85)	(0.45)	(0.38)	(0.99)
Lender Controls	Y	Y	Y	Y	Y	Y
Country Macro Controls	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y			
Number of Observations	15,502	15,502	15,502	9,580	8,594	8,593
R-Squared	0.17	0.20	0.07	0.17	0.18	0.09

Table A9 – Government Bond Holdings Controls from Euro-Zone Banks Stress Tests

This table shows OLS regressions of the effect of a sovereign downgrade on the total number of loans, the number of loans as a lead arranger, and the amount of loans as a lead arranger for banks that have a rating equal to or above the sovereign. This table includes additional controls for the holdings of government bonds by banks in the European Union. Bank and country controls are otherwise the same as in Table 3 and Table 4. Observations are at the lender-quarter level and the sample includes only observations after 2007, the only period for which we have data from the European Banking Authority. Panel A includes all borrowers, and Panel B uses only loans to foreign borrowers. The first three columns in each panel use a fixed effects model like the one in Table 3, and the last three columns use growth rates as the dependent variable (as in Table 4). All columns include quarter and country fixed effects. Standard errors are clustered at the country level. *, **, *** denote statistical significance at the 10, 5, and 1% levels, respectively.

Panel A – All Loans

	Level			*Growth*		
	Total Number of Loans	Number of Loans as Lead	Amount of Loans as Lead	Total Number of Loans	Number of Loans as Lead	Amount of Loans as Lead
	(1)	(2)	(3)	(4)	(5)	(6)
Lender Rating >= Sovereign Rating	-0.15	-0.29	-1.71*	0.07	0.06	0.27**
	(0.17)	(0.19)	(0.93)	(0.12)	(0.10)	(0.12)
Sovereign Downgrade	0.13*	0.10	0.18	0.02	0.06	0.12
	(0.08)	(0.09)	(0.63)	(0.15)	(0.16)	(0.31)
Lender Rating >= Sov. Rating x Sov. Downgrade	-0.10	-0.02	-1.36	-0.27***	-0.23**	-0.43**
	(0.16)	(0.17)	(1.58)	(0.10)	(0.10)	(0.19)
Exposure to Own Country	-1.85	-4.72	-17.04	-0.41	-0.37	-3.14**
	(5.54)	(4.93)	(18.99)	(0.72)	(0.56)	(1.28)
Lender Controls	Y	Y	Y	Y	Y	Y
Country Macro Controls	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y			
Number of Observations	848	848	848	779	761	760
R-Squared	0.18	0.18	0.05	0.25	0.20	0.15

Panel B – Loans to Foreign Borrowers

	Level			*Growth*		
	Total Number of Loans	Number of Loans as Lead	Amount of Loans as Lead	Total Number of Loans	Number of Loans as Lead	Amount of Loans as Lead
	(1)	(2)	(3)	(4)	(5)	(6)
Lender Rating >= Sovereign Rating	0.07	-0.04	-0.58	0.05	0.07	0.25
	(0.17)	(0.20)	(1.04)	(0.10)	(0.12)	(0.18)
Sovereign Downgrade	0.17*	0.11	0.31	-0.11	-0.11	-0.09
	(0.10)	(0.08)	(0.74)	(0.13)	(0.14)	(0.19)
Lender Rating >= Sov. Rating x Sov. Downgrade	-0.33*	-0.25	-2.84	-0.25*	-0.10	-0.21
	(0.19)	(0.20)	(1.97)	(0.15)	(0.24)	(0.48)
Exposure to Own Country	-1.19	-1.25	19.12	-0.52	0.44	-1.45
	(5.05)	(4.40)	(23.29)	(0.45)	(0.60)	(1.35)
Lender Controls	Y	Y	Y	Y	Y	Y
Country Macro Controls	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y			
Number of Observations	848	848	848	746	719	719
R-Squared	0.19	0.17	0.05	0.26	0.24	0.11

EXPORTING LIQUIDITY:

BRANCH BANKING AND FINANCIAL INTEGRATION*

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ABSTRACT

Using exogenous deposit windfalls from oil and natural gas shale discoveries, we demonstrate that bank branch networks help integrate U.S. lending markets. We find that banks exposed to shale booms increase their mortgage lending in non-boom counties by 0.93% per 1% increase in deposits. This effect is present only in markets where banks have branches and is strongest for mortgages that are hard to securitize. Our findings suggest that contracting frictions limit the ability of arm's length finance to integrate credit markets fully. Branch networks continue to play an important role in financial integration, despite the development of securitization markets.

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I. INTRODUCTION

Over the past thirty years the banking system in the U.S. has gone through a significant transformation, relying more on capital markets and direct finance in funding loans and less on bank deposits. The U.S. mortgage market has been at the forefront of this transformation, with 52% of loans in 2011 financed by securitization markets, up from 12% in 1980.[1] Moreover, improvements in information technology have facilitated bank lending well outside of branch-based geographical domains (Petersen and Rajan, 2002). These changes have integrated local credit markets by allowing capital to flow more freely across markets. The greater role of external capital markets should have diminished the value of bank branch networks for lending. But despite these changes, the extent and density of bank offices and branches has continued to grow, from 63,200 (about 5 per bank) in 1990 to 89,800 (about 14 per bank) in 2012.[2]

In this paper, we study the role of branch networks in integrating segments of credit markets where arm's length financing, such as securitization, has been limited by agency and information frictions. We exploit exogenous shocks to the supply of local bank deposits and detailed loan-level data to trace how these liquidity shocks propagate across markets. We document that banks increase their lending by 0.93% per 1% increase in deposits. This effect, however, is evident *only* in markets where banks have a branch presence. Moreover, the effect is concentrated in loans that are subject to more contracting frictions, and therefore are harder to fund from external markets (e.g., through securitization). These results provide 'smoking gun' evidence that branch networks allow lenders to mitigate contracting frictions, and play an important role in financial integration.

[1] These statistics refer to the whole mortgage market, including mortgages for home purchase, home equity lines, as well as mortgage re-financings.

[2] See http://www2.fdic.gov/hsob/HSOBRpt.asp.

Why might local deposit supply affect credit? Absent contracting frictions, changes in deposits should not affect loan supply; banks would already make all profitable loans. Lenders could finance the marginal loan either by borrowing in capital markets, selling the loan to other investors, or securitizing the loan. In such a world, home buyers themselves would be able to borrow anywhere, thus making the local pool of savings irrelevant for credit conditions. Bank branches would exist solely to provide convenience to depositors.

Contracting frictions, however, may constrain arm's length finance, either because lenders have better information than investors or because incentives for lenders to monitor diminish if a loan is sold (e.g., Gorton and Pennacchi, 1995, Holmstrom and Tirole, 1997, Keys et al, 2010). Adverse selection, for example, limits securitization for loans made by lenders with clear informational advantages over potential secondary market buyers (Loutskina and Strahan, 2011). If a branch presence lowers the cost of information production or allows better monitoring of distressed properties, then local deposits could be important for credit supply. In line with this argument, we evaluate whether local deposit shocks increase the availability of credit across all of a lender's markets. We then test whether branch presence plays an important role in the propagation of these shocks due to reducing information frictions. Finally, we test whether deposit windfalls have their greatest effect on loans that are harder to finance through external capital markets due to contracting frictions (e.g., home equity loans that are subordinated).

We exploit an exogenous positive shock to bank deposits caused by mineral royalty payments to local landowners for the development of shale gas by oil and gas companies. These payments increase deposits at banks with branches in shale-boom counties (Gilje, 2011 and Plosser, 2011). Prospecting and development for shale has resulted in 327 banks receiving deposit windfalls in different years between 2003 and 2010 as new discoveries were made. Consistent with the unexpected nature of these discoveries, we find no evidence that banks with a greater need of funds to support loan growth establish new branches in counties experiencing shale booms.

Armed with this exogenous deposit shock, we evaluate its effects on mortgage lending in counties connected to shale booms via bank branch networks. We focus on lending growth *outside* of shale-boom counties. Thus, our sample selection alleviates concerns that lending is being driven by the direct effects of shale discoveries on credit demand. Exploring mortgage lending is advantageous for two reasons. First, these loans have a clear geographical dimension pinned down by the property location, which is not possible for other types of loans. Second, the rich dataset allows us to saturate the model with county*year fixed effects, thus removing all potentially confounding demand effects. Conceptually, our regressions compare mortgage growth rates for two otherwise similar banks for properties located in the same county-year, one bank having branches in a shale-boom county (and thus getting a positive external liquidity shock) and the other having no branches in shale-boom counties.

In our first set of tests, we estimate the elasticity of mortgage lending with respect to deposits in an IV setting. We find that a one percent increase in deposits results in 0.93% increase in mortgage originations. More importantly, the estimated elasticity of lending growth to deposit growth is much larger for retained mortgages (2.27%), where banks' liquidity should matter. We find no effect of deposit growth on sold mortgages, as these are funded by national capital markets (rather than a bank's deposits). These results suggest that banks export deposits to non-booming markets and increase credit supply rather than merely retain more loans.

We then evaluate how the effect of the shocks differs with market and mortgage characteristics. We simplify the empirical set-up by estimating reduced form models, which allow us to add interaction effects that would be difficult to estimate in the IV setting. Consistent with the idea that a physical presence reduces contracting frictions (e.g., Berger et al, 2005), we find that banks experiencing deposit windfalls increase mortgage lending *only* in outlying (non-boom) counties where they have branches. They do not lend more in areas where they have no branch presence and thus have no advantage over the other sources of financing (e.g. securitization).

To further support this notion, we document that deposit windfalls expand lending more in segments subject to greater contracting frictions, which are less likely to be securitized, such as home equity lines (sold or securitized 4.5% of the time) and home-purchase mortgage (sold or securitized 46% of the time), as opposed to mortgage re-financings (sold or securitized 65% of the time). Arguably, the deposit windfalls could be financing bad loans, as managers waste the unexpected funds on pet projects (Jensen, 1986). While this agency based explanation is hard to rule out completely, we provide evidence inconsistent with it.

Our findings contribute to three strands of the literature. First, the results extend research on the financial integration of U.S. markets and help explain why large benefits followed deregulation.[3] Two mechanisms, potentially working in parallel, can explain why the removal of restrictions on banks' ability to expand across geographical markets improved economic outcomes: tougher competition and improved capital mobility. There is abundant evidence that

[3] The intrastate branching deregulation led to faster growth of the state economies (Jayaratne and Strahan (1996)) and lower growth volatility (Morgan, Rime and Strahan (2004)). Such deregulation came with better quality lending (Jayaratne and Strahan, 1996), more entrepreneurship and a greater share of small establishments (Black and Strahan 2002; Cetorelli and Strahan, 2006, Kerr and Nanda, 2009), lower income inequality, less labor-market discrimination and weaker labor unions (Black and Strahan, 2001; Beck et al, 2010; Levkov, 2012).

increases in competition post-deregulation led to more efficient banking (Stiroh and Strahan, 2003), lowered the cost of capital for non-financial firms (Rice and Strahan, 2010) and contributed to better allocation of resources (Jayaratne and Strahan, 1996). There is much less evidence, however, about deregulation's effect on capital mobility. In this paper, we show that branch networks contribute to the integration of local credit markets. Thus, the increasing scope and density of bank branch networks that followed deregulation potentially allows savings in areas with a relative dearth of good projects to finance investment in areas with higher-return projects.

Second, extant research evaluates whether close proximity between borrowers and lenders lowers the cost of information production and monitoring. Breakthroughs in information technology allowed for larger distances between borrowers and lenders (Petersen and Rajan, 2002). However, local lenders still extend more credit to riskier borrowers than distant lenders: loan rates tend to decline with the distance between borrower and lender (Degryse and Ongena, 2005; Agrawal and Hauswald, 2010); more opaque (smaller) borrowers tend to establish enduring relationships with their local (small) banks; and larger, more transparent firms tend to borrow from larger (not so local) financial intermediaries (e.g., Berger et al, 2005). In mortgage finance, locally concentrated lenders focus on soft information intensive segments of the mortgage market (Loutskina and Strahan, 2011) and have an advantage in screening and monitoring riskier borrowers (Cortes, 2011). We contribute to this literature by documenting that even in the most developed, integrated, and technologically advanced lending market (the U.S. mortgage market), local branching networks - and by extension local knowledge - remain important for segments of the credit markets subject to contracting frictions.

Finally, we offer a novel identification strategy to test whether and how bank liquidity shocks affect credit supply.[4] The extant literature offers different empirical designs to avoid confounding effects of credit demand or unobserved productivity shocks. Some studies exploit cross-sectional differences in bank on-balance-sheet lending responses to aggregate liquidity shocks from monetary policy (e.g., Gertler and Gilchrist, 1994, Kashyap et. al., 1994, Kashyap, Stein, 2000, Campello, 2002 and Loutskina, 2011). Others use natural experiments, where external shocks from abroad propagate into domestic credit markets through cross-border ownership of banks (e.g., Peek and Rosengren, 1997, Schnabl, 2012, Cetorelli and Goldberg, 2012). Our study is closest to those evaluating how local liquidity shocks from bank failures, government interventions or bank runs affect lending supply (Ashcraft, 2006, Khwaja and Mian, 2008, Paravisini, 2008, Iyer and Peydro, 2011). We analyze how a positive exogenous liquidity shock propagates to other markets and document the on-balance-sheet and aggregate lending supply elasticities with respect to deposit growth. We isolate supply effects by exploiting data with precise information on the location of both lender (branch location) and borrower (property location).

In the remainder of the paper, Section II describes briefly the shale booms and their effects on local banks. Section III describes our data, and Section IV reports empirical methods and results. Section V contains a brief conclusion.

II. SHALE BOOMS

In 2003, a surprise technological breakthrough combined horizontal drilling with hydraulic fracturing ("fracking") and enabled vast amounts of natural gas shale to become

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[4] See the theoretical arguments in, e.g., Bernanke and Blinder (1988), Holmstrom and Tirole (1997), and Stein (1998).

economically profitable to develop. Subsequent prospecting activity led to the development of a new energy resource equivalent to 42 years of U.S. motor gasoline consumption. As recently as the late 1990s, these reserves were not thought to be economically viable, and represented less than 1% of U.S. natural gas production.

The breakthroughs in the development of the Barnett Shale near Fort Worth, TX in 2003 changed industry notions on the viability of natural gas shale. The Barnett Shale was initially drilled by Mitchell Energy in the early 1980s (Yergin, 2011). Rather than encountering the highly porous rock of a conventional formation, however, Mitchell encountered natural gas shale. While shale holds vast amounts of natural gas, it is highly non-porous and traps the gas in the rock. After 20 years of experimentation, in the early 2000s Mitchell Energy found that hydraulic fracturing ("fracking") could break apart shale and free natural gas for collection at the surface. This breakthrough combined with new technology for horizontal drilling and higher natural gas prices made large new reserves from shale economically profitable to develop.

The size of this energy resource and the low risk of unproductive wells ("dry-holes") has led to a land grab for mineral leases. Before commencing any drilling operations, oil and gas firms must negotiate leases with mineral owners. Typically these contracts are comprised of a large upfront "bonus" payment, paid whether the well is productive or not, plus a royalty percentage based on the value of the gas produced over time. The resulting wealth windfalls led to large increases in local bank deposits. In an interview with the Houston Chronicle (2012), H.B. "Trip" Ruckman III, president of a bank in the Eagle Ford shale, stated "We have had depositors come in with more than a million dollars at a whack." This statement is consistent with reports of leasing terms. For example, an individual who owns one square mile of land (640 acres) and leases out his minerals at $10,000/acre would receive an upfront one-time payment of $6.4 million plus a monthly payment equal to 25% of the value of all the gas produced on his lease.

The deposit windfalls experienced by banks with branches in boom counties were exogenous to the underlying characteristics of the affected communities for a number of reasons. First, the technological breakthroughs, horizontal drilling and hydraulic fracturing, were unexpected, and the viability of these technologies in different geographies was uncertain. Highlighting the fast paced and unexpected nature of these discoveries, the New Orleans' Times-Picayune (2008) reported an increase in lease bonus payments from a few hundred dollars an acre to $10,000 to $30,000 an acre in the Haynesville Shale area within a one year time period. Second, the economic viability of the wells was determined by larger macroeconomic forces, such as demand for natural gas and natural gas prices (Lake, Martin, Ramsey, and Titman(2012)), and therefore was unrelated to the local economic conditions (health, education, demographics, etc.). Third, because fracking was a relatively new technology, predicting how many wells in an area might be needed to develop recoverable resources was challenging. These characteristics together suggest that it was unlikely that banks could strategically alter branch structures to gain greater exposure to shale windfalls. Thus, bank deposit windfalls from shale discoveries are an attractive setting to study the role of branch networks in financial integration.

III. DATA AND SAMPLE SELECTION

Our sample is based on lending activity in the seven states with major shale discoveries during the 2003-2010 time period: Arkansas, Louisiana, North Dakota, Oklahoma, Pennsylvania, Texas and West Virginia. As Figure 1 shows, each state contains a large number of counties that experienced shale booms as well as a large number of non-boom counties. Across the seven states, 124 counties experienced booms and 515 did not. Our sample, built at the bank-county-year level, includes all banks making housing-related loans (home purchase mortgages, mortgages for re-financing, and home equity loans) in any of these seven states. We consider all lenders irrespective of their branch locations (i.e., including loans originated without brick and mortar presence in a county) or exposure to the booms. We drop all non-bank lenders because most fund mortgage lending with securitization and are thus not affected by local liquidity shocks. The sample begins in 2000 (three years before the first shale boom), and ends in 2010.

Using the *Summary of Deposits* from the Federal Insurance Deposit Corporation (FDIC), we determine the number of branches and amount of deposits held by each bank in each county-year in the seven states.[5] These data allow us to build two alternative measures of exposure to the shale-boom shocks. The first - *Share of Branches in Boom Counties* - equals the fraction of branches owned by each bank that are located in a shale-boom county. The measure ranges from zero (for banks without branches in boom counties, or for banks with branches in boom counties during the years prior to a boom's onset) to one (for banks with all of their branches in boom counties after the onset of the booms). This variable equals zero for all bank-years prior to 2003, the year of the first shale investment. After 2003, the variable increases within bank over time as more counties experience booms.

Our second measure accounts for both the distribution of branches across counties as well as the size of the shale investments (as a proxy for the amount of money being deposited into local branches). This measure – *Growth in Shale Well Exposure* - equals the weighted exposure to the growth in the number of shale wells, where the fraction of a bank's branches in each county serves as weights. This measure is harder to interpret than the *Share of Branches in*

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[5] http://www2.fdic.gov/sod/.

Boom Counties - it need not vary between zero and one - but it accounts for differences in the relative size of the booms.

Our models focus on the effect of exposure to the shale boom on mortgage credit growth, but we include other bank characteristics as control variables, each measured from the end of the prior year. These variables include the following: Log of $Assets_{t-1}$; $Deposits/Assets_{t-1}$; Cost of $Deposits_{t-1}$ (=interest expenses on deposits / total deposits); Liquid Assets / $Assets_{t-1}$; Capital / $Assets_{t-1}$ (=Tier 1 capital/ assets); C&I Loans / $Asset_{t-1}$; Mortgage Loans / $Assets_{t-1}$; Net Income / $Assets_{t-1}$; Loan Commitments / $Assets_{t-1}$; and, Letters of Credits /$Assets_{t-1}$. Data for bank control variables come from year-end Call Reports. We merge Call Report and HMDA as in Loutskina and Strahan (2009).

Table 1 reports summary statistics for our two measures of banks' exposure to the shale well boom - *Share of Branches in Boom Counties* and *Growth in Shale Well Exposure* (Panel A), as well as the lagged bank characteristics (Panel B), separated by whether or not the bank has any exposure to a shale-boom county. Table 1 shows that exposed banks tend to be larger than non-exposed banks and that their deposits grow faster, consistent with the notion that exposure to the shale boom leads to strong deposits inflows. The marked difference in asset size (log of assets) is a potential concern in our models because large banks differ in many ways from smaller ones, so we will report robustness tests in which we filter out larger banks.

To measure mortgage activity, we utilize the detailed data on mortgage applications collected annually under the *Home Mortgage Disclosure Act* (HMDA). Whether a lender is covered depends on its size, the extent of its activity in a Central Business Statistical Area

(CBSA), and the weight of residential mortgage lending in its portfolio.[6] The HMDA data include loan size, whether or not a loan was approved, as well as some information on borrower characteristics. Using HMDA data, we measure mortgage origination growth by bank-county-year. HMDA reports both the identity of the lender as well as the location of the property down to the census-tract level. These are the only comprehensive data on lending by US banks that allow researchers to locate borrowers geographically. In principle we would also like to test for similar effects on other kinds of loans (especially loans to small businesses), but micro data at loan level are not available outside of housing. HMDA also contains information on the purpose of the loan (mortgage purchase loans, home-equity loans, and mortgage re-financings) and whether the lender expects to sell or securitize the loan within one year of origination. We use these data to test whether loans easier to finance in securitization markets respond less to the local deposit inflows that follow shale booms.

Panel C of Table 1 reports summary statistics for the mortgage growth rates. For the average exposed bank, mortgages grow 11.7% per year, compared to 11.2% for banks not exposed. This difference is larger for retained mortgage growth, which averages 9.1% per year for exposed banks, compared to 7.7% for non-exposed banks. These raw differences could be attributed to both the deposit windfalls as well as to economic growth of the boom counties. We isolate these two effects in our regressions. Note that the standard deviation in the mortgage growth rates is very high relative to the mean, but most of this variation reflects time-series fluctuations stemming from changes in interest rates (which alter re-financing rates drastically)

[6]Any depository institution with a home office or branch in a CBSA must report HMDA data if it has made a home purchase loan on a one-to-four unit dwelling or has refinanced a home purchase loan and if it has assets above $30 million. Any non-depository institution with at least ten percent of its loan portfolio composed of home purchase loans must also report HMDA data if it has assets exceeding $10 million. Consequently, HMDA data does not capture lending activity of small or rural originators. U.S. Census shows that about 83 percent of the population lived in metropolitan areas over our sample period and hence the bulk of residential mortgage lending activity is likely to be reported under the HMDA.

as well as variation around the housing boom (2004-2006) and bust (2006-2010) periods, which our data straddle.

HMDA also contains some borrower characteristics, which we use to build the following control variables for all loans originated at the bank-county-year level: borrower and area income, loan size-to-borrower-income ratio, percent women and percent minority, and percent minority in the area for loans. In all of our models we control for the contemporaneous means of each of these borrower attributes across all loan originations in a given bank-county-year.

IV. METHODS AND RESULTS

Instrumental Variable Analysis

To test how deposit shocks affect lending, we estimate the following relationship:

$$\textit{Mortgage Growth}_{i,j,t} = \alpha_{j,t} + \beta \cdot \textit{Deposit Growth}_{i,t} + \textit{Borrower \& Lender Controls} + \varepsilon_{i,j,t}\,, \quad \textbf{(1)}$$

where *i* indexes lenders, *j* indexes counties, and *t* indexes years. The county*year fixed effects ($\alpha_{j,t}$) remove time-varying, county-level demand-side shocks related to business cycles, industry composition, housing demand, etc. To further separate supply shocks from potentially confounding demand shocks, we include in our sample *only* counties that *did not* experience a shale boom during the 2000-2010 period.

We use two alternative measures of a bank's exposure to the shale booms as instrumental variables for deposit growth: *Share of Branches in Boom Counties* and *Growth in Shale Well Exposure*. Unlike the growth in lending volume, the measures of deposit growth, as well as the instruments, do not vary across counties for a given bank-year. Since, there could be common, time-invariant bank-level components to the error term, we build standard errors by clustering by bank throughout all of our results.

We first model total mortgage originations growth as the dependent variable, and then we decompose *Mortgage Growth*$_{i,j,t}$ into the growth in retained mortgages and the growth in sold or securitized mortgages. This decomposition offers a number of advantages. First, it allows us to document the true on-balance-sheet elasticity of total lending to a deposit supply shock. Second, it allows us to evaluate whether a deposit shock leads banks to retain more loans at the expense of the secondary market. The ability of the capital markets to absorb securitized loans should not be affected, but a bank's willingness to supply such loans to the secondary market might change with their financial conditions. Finally, the decomposition allows us to further validate our identification strategy.

Table 2 reports the IV and OLS estimates of (1). Columns (1) and (2) contain first-stage results, one using *Share of Branches in Boom Counties* and the other using *Growth in Shale Well Exposure*. As expected, deposits grow faster at banks with a greater fraction of branches in shale-boom counties. The instrument has a t-statistic of 1.97 (column 1) or 3.10 (column 2); in both cases we pass the Kleibergen-Paap weak identification test and the Anderson-Rubin Chi-square and F-tests for significance of endogenous regressors. Since the model is just identified, we cannot report over-identification tests. Columns (3), (5) and (7) report the OLS versions, and columns (4), (6) and (8) report the IV estimates for comparison. The reported IV analysis corresponds to the first-stage equation in column (1). The IV results based on *Growth in Shale Well Exposure* instrument are qualitatively and quantitatively similar.

Notably, the OLS coefficients are positive and significant with very similar magnitudes across all three mortgage-growth variables, ranging from about 0.4 to 0.6. However, when we isolate the deposit supply-shock channel, we observe significantly different elasticities across the three loan categories. The supply shock leads to an increase in overall lending activity, with a one percent increase in bank deposits leading to a 0.93 percent growth in loan origination. This effect comes mostly from banks originating and retaining more loans but not at the expense of securitizing less. The coefficient suggests that a one percent increase in deposit growth (from an external liquidity supply shock) causes a 2.3 percent increase in the growth of retained mortgages. An elasticity above one implies that other portions of the bank's balance sheet, such as investments in securities or other liquid assets, are not affected or even decline when deposit supply expands. Investments in liquid assets, for example, may decline in response to the shale-boom windfalls, although we have no clean way to identify this relationship because such investments have no geographical component. Overall, these results suggest that a deposit inflow expands lending rather than merely redistributing loans away from the securitization market and onto banks' balance sheets.

Unobserved bank characteristics are unlikely to be able to explain our key results. The bank-year level control variables in Table 2 have relatively little explanatory power in these regressions. Moreover, the results of interest are similar when these variables are excluded (not reported).

Do Banks Enter 'Boom' Counties to Chase Funds?

One concern may be that, after observing the advent of shale-boom discoveries in 2003, banks strategically enter shale-boom counties (or counties with known shale reserves) to raise low-cost deposits. If such entry were motivated by the need to fund loans, then our effects could be driven by *both* supply and demand factors, thus invalidating our identification strategy. [7]

[7] For example, Ben-David, Palvia and Spatt (2013) report evidence of banks increasing demand for deposits (and hence prices) locally when they face higher loan demand in out-of-state markets connected through branches.

We address this concern by directly testing whether banks with higher loan demand subsequently increase their exposure by entering shale-boom counties. Specifically, we evaluate what share of a bank's boom exposure measures is attributed to its 2002 branch distribution and whether bank-specific loan demand affects the remaining variation in exposure. The distribution of branches in 2002 could not have been motivated by demand for funds by banks because shale booms started unexpectedly in 2003. We build the 2002-branch-network exposure proxies using only the time variation in county shale booms (*Share of 2002 Branches in Boom Counties*$_{i,t}$ and *Growth in Exposure from 2002 Branches*$_{i,t}$). These measures capture exposure to the boom that would have occurred if each bank had held constant its 2002 branch network. We then run the following regression specifications:

$$\begin{aligned} &\textit{Share of branches in boom counties}_{i,t} = \gamma_1 \bullet \textit{Share of 2002 Branches in Boom Counties}_{i,t} + \\ &\qquad \gamma_2 \bullet \textit{Mortgage Growth}_{i,t-1} + \gamma_3 \bullet \textit{Mortgage Growth}_{i,t-2} + \textit{Control Variables} + \varepsilon_{i,t}, \qquad \textbf{(2a)} \end{aligned}$$

and

$$\begin{aligned} &\textit{Growth in Shale Well Exposure}_{i,t} = \gamma_1 \bullet \textit{Growth in Exposure from 2002 Branches}_{i,t} + \\ &\qquad \gamma_2 \bullet \textit{Mortgage Growth}_{i,t-1} + \gamma_3 \bullet \textit{Mortgage Growth}_{i,t-2} + \textit{Control Variables} + \varepsilon_{i,t}, \qquad \textbf{(2b)} \end{aligned}$$

where the unit of observation is bank *i* – year *t*.

If banks' exposure to the boom is solely due to the time variation in onsets of boom throughout the counties, then we expect γ_1=1. If banks facing higher loan demand (captured by past loan or application growth) enter booming markets to access cheap deposits, then we expect $\gamma_2 > 0$ and/or $\gamma_3 > 0$. We estimate (2a) and (2b) over the 2003 to 2010 period because these are the years when the shale booms occur. The sample contains all banks that originated mortgages in at least one county in the seven states that experience shale booms.

Table 3 reports the estimates of (2a) in Panel A and (2b) in Panel B with different sets of control variables. The 2002 branch distribution explains the vast majority of subsequent exposure to the shale booms. In the simple models, R^2 exceeds 92%. Moreover, t-statistics on *Share of 2002 Branches in Boom Counties (Growth in Exposure from 2002 Branches)* never fall below 50. At the same time, past loan growth has almost no explanatory power. Even in column (2) of Panel B, where the coefficient γ_3 is statistically significant at the 10% level, the effect of past loan growth on boom exposure is economically negligible. Since loan growth may be an imperfect proxy for loan demand, in an unreported set of tests we find that the past growth in loan *applications* also does not explain the residual variation in banks' shall boom exposure measures. Overall, there is no evidence that banks with high loan demand systematically enter (or purchase branches in) shale-boom counties.

Reduced Form Approach

We have established that lending growth responds positively to deposit windfalls from external markets. In the remainder of the paper we evaluate which markets and loan types benefit most from the windfalls from shale-boom exposure. To explore these questions we simplify the empirical set-up and focus on reduced forms linking a bank's shale-boom exposure to its lending in non-shale counties. The reduced form approach allows us to test for interaction effects, which would be difficult to estimate in the IV setting. As a first step, however, we present the reduced form models that correspond to the instrumental variable analysis presented in Table 2 and evaluate the robustness of our core results. The baseline reduced form model is as follows:

$$Mortgage\ Growth_{i,j,t} = \alpha_{j,t} + \beta\ Bank\ Boom\ Exposure_{i,t} + Borrower\ \&\ Lender\ Controls + \varepsilon_{i,j,t}\,. \quad \mathbf{(3)}$$

Table 4 reports the results. Consistent with the instrumental variable analysis (Table 2), we find significant positive effects of exposure to shale-booms on both total mortgage growth (columns 1 & 2) and growth of retained mortgages (columns 3 & 4), but no significant effect on sold-loan growth (columns 5 & 6). For retained mortgages, a typical exposed bank (e.g. one with about 45% of its branches in a shale-boom county – recall Table 1) would grow its retained-mortgage portfolio 14 percentage points (=0.45*0.325) faster in the non-boom counties than a similar bank without exposure to the shale-boom windfalls (based on the coefficient of interest in column 3). Similar to Table 2, the bank-year level control variables have relatively little explanatory power and the coefficients of interest are similar when these variables are excluded.

Furthermore, our reduced form model results withstand a wide set of robustness tests presented in Table 5. First, we evaluate whether our results could be attributed to the shale-boom exposed banks systematically lending more irrespective of the boom. That is, we test whether the parallel trends assumption between 'treatment' and 'control' banks is violated. Columns (1) and (2) of Table 5 test whether banks exposed and not exposed to booms behave similarly before the booms actually occur. We create the variable *Pre-boom Indicator for Booming Banks,* equal to one for booming banks during all years prior to an actual boom. For example, the indicator would be set equal to one during 2000-2006 for a bank that first became exposed to a shale-boom county in 2007. The indicator would be equal to zero for all years after 2006 in this example. For banks that never experience exposure, the indicator equals zero for all years. By introducing this variable, we can rule out the possibility that banks which experience booms (the treatment group) behave differently from other banks (control group) during 'normal' times. Consistent with this notion, the coefficient on this variable is never significant.

Second, we rule out the possibility that our results are driven by banks whose branches happen to be closer to shale-boom counties grow faster than other banks in the same county. If some banks' lending grows faster due to demand spill-overs from neighboring boom counties, then our results could be driven by both supply- and demand-side shocks. We evaluate the validity of this hypothesis by simply dropping all counties that abut boom counties (columns 3 and 4). The results are similar to those reported in our baseline models and further support the notion that the elasticities we document are supply-side driven.

Third, the summary statistics presented in Table 1 indicate that the exposed banks tend to be larger than those never exposed to shale booms. The disparity occurs because large banks, by the very fact that they are large, will have a greater likelihood of having at least some exposure to counties with shale-booms. Large banks, however, also have wide access to the capital markets and, during the time of crisis, government financial support, and hence might grow their lending quicker than the rest of the banking sector. To evaluate this premise, we estimate equation (3) without banks with a very small (but non-zero) exposure to the boom counties (less than 2.5%). This filter removes the large, nationwide banks that are unlikely to be affected in a significant way by local variation in deposits. Moreover, when we impose this filter the average asset size for exposed vs. unexposed banks becomes very close ($400 vs. $465 million), as opposed to the unfiltered data (recall Table 1). The coefficients on both *Share of Branches in Boom Counties* and *Growth in Shale Well Exposure* increase in magnitude and statistical significance when we impose this filter (0.17 v. 0.15 in column (5); 0.06 v. 0.05 in column (6)).

Fourth, we estimate equation (3) after dropping bank-county-years where the mortgage growth rate is based on fewer than 15 loans during the prior year (columns (7) and (8)). This filter drops observations likely to have substantial noise in the dependent variable. Again, the results are stronger than before, both in terms of magnitudes as well as statistical significance. This indicates that our results cannot be attributed to noise in measuring the changes in banks' origination decisions.

In the fifth and final robustness test, we add bank*county fixed effects (columns (9) and (10)). Adding these removes the possibility that some banks may always grow faster than others within the same county. For example, some banks may simply have more advertising in specific areas or branches in better locations, leading to persistently higher rates of mortgage growth. In fact, adding the bank*county effects increases the magnitude and statistical significance of our results.

Note that in Table 5 and hereafter, we focus on total mortgage origination, although as we have documented the effects are driven by variation in retained (as opposed to sold) mortgage growth. The core focus of this paper is to evaluate whether bank deposit inflows affect overall lending supply as opposed to exploring the shocks' effects on a bank's decision to finance lending on balance sheet or through loans sales/securitization. Loutskina and Strahan (2009) have established that the decision to hold or sell a mortgage at the margin depends on a bank's funding cost, which varies with exposure to the shale booms in the setting of this paper.

Where Do Local Shocks Matter?

Theory suggests that an increase in deposits should only affect credit supply for loans where contracting frictions make arm's length finance difficult, either because lenders have better information than investors or because incentives for lenders to engage in sufficient monitoring would diminish if a loan were sold (e.g., Gorton and Pennacchi, 1995, Holmstrom and Tirole, 1997, Keys et al, 2010). If a lender has no information or monitoring advantage relative to any other lenders – if the lending decision depends only on public information such as borrower FICO scores and mortgage loan-to-value ratios – then we would expect changes in bank funding to have no impact on their credit supply decisions. These markets would be highly commoditized and competitive.

In contrast, changes in local funding could affect credit supply in market segments where frictions require soft information production and thus erect barriers to non-local lenders or to local lender securitizing their originations. In line with these arguments, we should see deposit inflows being exported to markets with more contracting frictions and those where lenders have informational advantage over the other financial intermediaries.

Based on these ideas, we first evaluate whether deposit windfalls increase lending more in counties where banks have branches, as compared to counties where they lend without a brick and mortar presence. Extant literature suggests that local lenders have an informational advantage as they tend to lend to more opaque and riskier firms. Mortgage lenders with branches near their borrowers also have an advantage in monitoring borrowers that may experience distress. Figure 2 further validates the underlying assumption that a local branch presence allows banks to produce more soft information about borrowers by presenting securitization rates for mortgage loans made in the seven states that we study. Specifically, it compares loans originated by banks with (local) and without (non-local) a branch in the same county as the property being financed. These figures show that mortgages made by local lenders are consistently securitized or sold at much lower rates than those made by non-local lenders; the difference is nearly 30 percentage points, on average.[8]

[8] A natural way to sort our data would be based on whether or not Fannie or Freddie will provide credit guarantees, such as comparing jumbo and non-jumbo mortgages. Unfortunately, the markets we study have low real estate prices so that the vast majority of loans fall into the non-jumbo category.

Second, we evaluate the effect of deposit windfalls by mortgage type. Contracting frictions should be most pronounced for home-equity loans (because these are often subordinated), and least for mortgage re-financing (because borrowers have an established payment history), with home purchase originations being between these two extremes. Consistent with this notion, securitization rates are lowest among home-equity loans (4.5%), highest among mortgage refinancing loans (65%), with mortgages for home purchase in the middle (46%).

So, we expect local lenders (those with branches in the same county as the borrower) to respond more to the deposit windfalls than non-local lenders. Similarly, we expect home-equity loan growth to respond most to the deposit shock, and re-financings least. To test these ideas, we first introduce an interaction to the reduced form models based on whether or not the bank has a branch located near the borrower:

$$\begin{aligned} \textit{Mortgage Growth}_{i,j,t} &= \alpha_{j,t} + \beta_1 \textit{Local Lender}_{i,j,t} + \beta_2 \textit{Bank Boom Exposure}_{i,t} + \\ &+ \beta_3 \textit{Local Lender}_{i,j,t} {*}\ \textit{Bank Boom Exposure}_{i,t} + \textit{Borrower, Lender Controls} + \varepsilon_{i,j,t} \qquad \textbf{(4)} \end{aligned}$$

In equation (4), *Local Lender*$_{i,j,\mathrm{t}}$ equals one if a lender i has at least one branch in county j in year t and zero otherwise. The coefficient β_3 can be interpreted as the relative difference in the effect of having a local branch versus providing the financing at arm's length. Columns (1) and (2) if Table 6 report results using all lenders, and includes the interaction term to identify β_3. Columns (3) and (4) of Table 6 report the model without the interaction term, including just the local-lender sample of bank-county-years.

We find mortgage growth increases for banks exposed to shale-boom windfalls, but *only* for local banks - those with branches in the same county as the property being financed. The interaction term is positive and significant (columns 1 and 2), and the overall impact on local banks is itself significant (columns 3 and 4). The direct effect of the deposit windfall, however, is not significant (columns 1 and 2), meaning that lending in counties where exposed banks do not have branches does not change. Comparing the typical local bank with exposure (*Share of Branches in Boom Counties* = 0.45, recall Table 1) to a local bank without exposure (*Share of Branches in Boom Counties* = 0), mortgage lending would grow 10 percentage points faster (=0.45*0.23, based on column 3) at the exposed bank. There is no evidence that lenders exposed to the shale-boom windfalls would supply more credit to geographies where they do not have branches (i.e. neither the direct effect of *Share of Branches in Boom Counties* nor *Growth in Shale Well Exposure* is significantly different from zero). Table 6 thus establishes that local windfalls stimulate lending only in markets connected through bank branching networks.

Next, we incorporate loan type by estimating Equation (4) separately for home equity loans, mortgages for home purchase, and mortgages for refinancing.[9] Table 7 reports only the coefficients of interest, but the specification includes the same set of borrower and lender controls and county*year fixed effects as the previous sets of results. Consistent with the earlier analysis, only local lenders respond to the deposit windfalls. Moreover, their response is evident only among loans that are hard to securitize (and subject to more contracting frictions): mortgages for home purchase and home equity loans, but not mortgages for re-financing. In these specifications, the effects of the deposit windfall are largest for the home-equity segment, intermediate for mortgages for home purchase, and zero for the re-financing segment.

[9] Samples differ across the three columns in Table 7 because we model the growth rate in lending, so a bank-county only appears if there are non-zero originations in two consecutive years.

Is New Mortgage Lending a Free-Cash-Flow Agency Problem?

Our results suggest that portions of the mortgage market where local knowledge limits the impact of securitization and arm's length finance respond to local liquidity shocks from deposit inflows. This increase, however, could reflect lender agency problems (Jensen, 1986) whereby unexpected cash inflows lead managers to over-invest and destroy value (i.e. marginal loans have NPV<0). The agency explanation is hard to rule out fully because we are not able to follow loan outcomes at the bank-county-year level. [10]

Instead, we consider lending in the boom counties themselves. If the windfalls are large, then all banks ought to be able to fully exploit profitable lending opportunities within the boom counties; thus, mortgage lending growth in the boom counties should not vary as a bank's access to external (non-boom) counties changes. On the other hand, if agency problems are motivating the increase in lending, then banks confined to boom counties without access to external lending markets (that is, banks with branches only in booming counties) would expand lending more than other exposed banks.

To test this idea, we add the boom counties to our panel and include interaction terms to allow the effects of *Bank Boom Exposure* proxies to vary depending on whether a county itself is experiencing a shale boom. Thus, we estimate the following regression:

$$Mortgage\ Growth_{i,j,t} = \alpha_{j,t} + \beta_1 Bank\ Boom\ Exposure_{i,t} + \qquad \textbf{(5)}$$
$$+ \beta_2 Boom\ County_{j,t} {*}\ Bank\ Boom\ Exposure_{i,t} + Borrower,\ Lender\ Controls + \varepsilon_{i,j,t}$$

[10] Loan-level data on delinquencies and foreclosures is available, but assessing which investor actually bears losses is not. For example, when loans that have been securitized (or loans where originators have purchased credit protection from one of the GSEs) go bad, losses may not affect the originating lender, or such losses may be shared with other investors.

where *Boom County*$_{j,t}$ is an indicator variable equal to one if county j in year t is experiencing a shale well boom and zero otherwise. The direct effect of the indicator variable *Boom-County*$_{i,t}$ is absorbed by the county-year effects. Thus, the results cannot be explained by the demand side shock associated with the onset of the shale boom in a county. For these tests, we include only local banks, since we have documented that only they adjust their lending in response to the shale-boom shocks.

As documented in Table 8, we find no significant relationship between the extent of connections to external markets and mortgage growth within the boom counties – all banks in these counties behave similarly with respect to local loan growth; for example: in column (1) the sum of the coefficient on *Share of Branches in Boom Counties* and the coefficient on its interaction with the *Boom-County* is approximately zero. Since all banks in boom counties are flush with deposits, they can fully exhaust their profitable loans there. In contrast, in the non-boom markets banks' increase in exposure to the deposit shock leads to increased lending. The effects estimated here are economically similar to those reported earlier for regressions that included just the non-boom counties. (These results are reproduced in Table 8, columns 3 & 4 for comparison.)

In addition, we provide two more tests to further confirm that the deposit inflows are allocated rationally by lenders. First, we test whether deposit inflows affect mortgage growth most in those markets with the highest un-served credit demand. If credit supply expands rationally to finance good projects (as opposed to managers' pet projects), we would expect a greater response in counties with more ex ante demand for credit. To measure un-served credit demand, we follow Mian and Sufi (2009), who argue that the advent of subprime credit had its greatest impact on neighborhoods with unmet demand for mortgage credit, based on the mean mortgage approval rate in the area at the beginning of their sample. Their analysis suggests that such areas experienced stronger growth in credit and housing prices, and then larger crashes after 2006. We apply their strategy to our setting by inter-acting our measure of external deposit windfalls with the average mortgage approval rate (based on HMDA data) from all mortgage applications made during the prior bank-county-year.

Second, we test whether financial constraints alter how banks react to the deposit windfalls. We introduce an interaction between our measures of exposure with the lag of the bank capital-asset ratio (known in regulatory parlance as the 'leverage ratio').[11] If credit expands rationally, banks with higher capital – banks less constrained by capital - can deploy their low-cost deposits to make more new loans; in contrast, more constrained banks would more quickly face binding regulatory capital constraints.

Table 9 reports these results, with each interaction term reported separately and then both together. (The direct effects of both the lagged approval rate and the lagged capital ratio are in the models but not reported.) Deposit windfalls spur lending most in areas with low mortgage approval rates, which we interpret as a proxy for un-satisfied demand for mortgage credit.[12] We find large differences in the movement of funds depending on our measure of unmet demand. For example, when demand is low (lagged approval rate = 90%), the coefficients in column 1 imply that exposed lenders (*Share of Branches in Boom Counties* = 0.45) increase their mortgage loans by 7.5 percentage points more than unexposed lenders. In contrast, when un-served credit

[11] We find similar results if we used the bank's ratio of Tier 1 capital to risk weighted assets.

[12] In fact, the lagged approval rate is strongly correlated with mortgage growth – markets with high approval rates grow more slowly, validating the interpretation of this variable as a measure of unmet credit demand – but adding this variable does not change the overall effect of the liquidity windfall variables.

demand in high (lagged approval = 50%), the exposed banks increase mortgages 22 percentage points faster than unexposed ones.

Financial constraints also affect the impact of the deposit shocks. Capital potentially limits the extent to which a bank may deploy a given inflow from branches located in shale-boom counties because banks must operate above regulatory required minimum capital ratios. Since capital is costly to increase in the short run, especially for small and medium sized banks without access to public markets, we would expect the impact of the shock to increase with the ratio of capital to assets.[13] Consistent with this notion, the interaction of *Share of Branches in Boom Counties* (*Growth in Shale Well Exposure*) with capital is positive and significant, both economically and statistically.

To understand magnitudes, consider first the difference in lending between exposed (*Share of Branches in Boom Counties* = 0.45) and non-exposed banks with high approval rates (=0.9, implying little un-served credit demand) and low capital (=0.07, one sigma below the mean). Our coefficients suggest that the exposed bank would grow its lending by just 2 percentage points faster than the non-exposed bank (using coefficients from column 3). Taking the other extreme, next consider the difference in lending between exposed and non-exposed banks with low approval rates (=0.5, implying substantial un-served credit demand) and high capital (=0.13, one sigma below the mean). In this case the coefficients suggest that the exposed bank would grow its lending 26 percentage points faster than the non-exposed bank. Thus, banks with high demand for credit that are able to deploy the deposit windfalls (due to high levels of ex ante capital) grow their mortgage portfolios very substantially.

[13] We have also tested other possible measures of a bank's financial constraints, such as asset size or holdings of liquid assets; these are not significantly related to the size of the liquidity shock's impact on mortgage growth.

V. CONCLUSIONS

We have provided evidence of the importance of bank branch networks in fully integrating segments of local credit markets that are subject to financial contracting frictions. Shale-boom discoveries provide large and unexpected liquidity windfalls at banks with branches nearby as mineral-rights owners deposit large amounts of their new wealth into local banks. Mortgage lending increases as these banks export the liquidity windfalls into outlying (non-boom) markets, but *only* when such banks have branches in *both* markets. Banks experiencing deposit inflows do not export liquidity and lend more in areas where they have no branch presence because, we argue, without a branch presence banks cannot collect soft information about the borrowers and thus have no advantage over securitization markets.

Our results provide 'smoking gun' evidence that bank branching fosters financial integration by allowing savings collected in one locality (shale-boom counties) to finance investments in another (non-boom counties). The result is important for two reasons. First, it demonstrates the limits to arm's length financing technologies like securitization in integrating financial markets. For credit markets that require lenders to locate near borrowers to adequately understand and monitor risk, securitization is not a viable financing mechanism. Second, by allowing capital to flow more easily across local markets, deregulation of bank branching fostered a denser branch network that improved capital mobility and thus investment allocation efficiency. Better quality investment can help explain why broad economic outcomes like growth and volatility improved after branching reform.

References

Agrawal, S., Hauswald, R., 2010, "Distance and Private Information in Lending," *Review of Financial Studies* 23, 2757-2788.

Ashcraft, A., 2006, "New Evidence on the Lending Channel," *Journal of Money, Credit, and Banking* 38, 751-776.

Beck, T., Levine, R., Levkov, A., 2010 "Big Bad Banks? The Winners and Losers from Bank Deregulation in the United States," *Journal of Finance* 65, 1637-1667.

Berger, A. N., Miller, N. H., Petersen, M. A., Rajan, R. G., Stein, J. C., 2005, "Does Function Follow Organizational For? Evidence from the Lending Practices of Large and Small Banks," *Journal of Financial Economics* 76, 237-269.

Bernanke, B. S., Blinder, A. S., 1988, "Credit, Money, and Aggregate Demand," *American Economic Review* 78, 435-439.

Black, S. E., Strahan, P. E., 2001, "The Division of Spoils: Rent-Sharing and Discrimination in a Regulated Industry," *American Economic Review* 91, 814-831.

Black, S. E., Strahan, P. E., 2002, "Entrepreneurship and Bank Credit Availability," *Journal of Finance* 57, 2807-2833.

Campello, M., 2002, "Internal Capital Markets in Financial Conglomerates: Evidence from Small Bank Responses to Monetary Policy," *Journal of Finance* 57, 2773-2805.

Cetorelli, N., Goldberg, L., 2012, "Bank Globalization and Monetary Policy," *Journal of Finance*.

Cetorelli, N., Strahan, P. E., 2006, "Finance as a Barrier to Entry: Bank Competition and Industry Structure in Local U.S. Markets," *Journal of Finance* 61, 437-461.

Cortes, K. R., 2011 "Did Local Lenders Forecast the Bust? Evidence from the Real Estate Market," Working Paper.

Degryse, H., Ongena, S., 2005, "Distance, Lending Relationships, and Competition," *Journal of Finance* 60, 231-266.

Gertler, M., Gilchrist, S., 1994, "Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms," *Quarterly Journal of Economics* 109, 309-340.

Gilje, E. P., 2011, "Does Local Access to Finance Matter? Evidence from U.S. Oil and Natural Gas Shale Booms," Working Paper.

Gorton, G. B., Pennacchi, G. G., 1995, "Banks and Loan Sales: Marketing Nonmarketable Assets," *Journal of Monetary Economics* 35, 389-411.

Holmstrom, B., Tirole, J, 1997, "Financial Intermediation, Loanable Funds, and the Real Sector," *Quarterly Journal of Economics* 112, 663-691.

Houston Chronicle, 2012, "Eagle Ford Banks Challenged as Deposits Skyrocket," June 8.

Iyer, R., Peydro, J., 2011, "Interbank Contagion at Work: Evidence from a Natural Experiment," *Review of Financial Studies* 24, 1337-1377.

Jayaratne, J., Strahan, P., 1996, "The Finance-Growth Nexus: Evidence from Bank Branch Deregulation," *Quarterly Journal of Economics* 111, 639-670.

Jensen, M., 1986, "Agency Cost of Free Cash Flow, Corporate Finance, and Takeovers," *American Economic Review 76*, 323-32.

Kashyap, A. K., Lamont, O. A., Stein, J. C., 1994, "Credit Conditions and the Cyclical Behavior of Inventories," *Quarterly Journal of Economics* 109, 565-592.

Kashyap, A., Stein, J. C., 2000, "What do a Million Observations on Banks Say About the Transmission of Monetary Policy," *American Economic Review* 90, 407-428.

Kerr, W. R., Nanda, R., 2009, "Democratizing entry: Banking Deregulations, Financing Constraints and Entrepreneurship," *Journal of Financial Economics* 94, 124-149.

Keys, B., Mukherjee, T., Seru, A., Vig, V., 2010, "Did Securitization Lead to Lax Screening: Evidence from Subprime Loans," *Quarterly Journal of Economics* 125, 307-362.

Khwaja, A. I., Mian, A., 2008, "Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market," *American Economic Review* 98, 1413-1442.

Lake, L. W., Martin, J., Ramsey, J. D., Titman, S., 2012, "A Primer on the Economics of Shale Gas Production," Working Paper.

Levkov, A., 2012, "Branching of Banks and Union Decline," Working Paper.

Loutskina, E., 2011, "The Role of Securitization in Bank Liquidity and Funding Management," *Journal of Financial Economics* 100, 663-684.

Loutskina, E, Strahan, P.E., 2009, "Securitization and the Declining Impact of Bank Finance on Loan Supply: Evidence from Mortgage Acceptance Rates," *Journal of Finance* 64, 861-889.

Loutskina, E., Strahan, P. E., 2011, "Informed and Uninformed Investment in Housing: The Downside of Diversification," *Review of Financial Studies* 24, 1447-1480.

Mian, A., Sufi, A., 2009, "The Consequences of Mortgage Credit Expansion: Evidence from the U.S. Mortgage Default Crises," *Quarterly Journal of Economics* 124, 1449-1496.

Morgan, D. P., Rime, B., Strahan, P. E., 2004, "Bank Integration and State Business Cycles," *Quarterly Journal of Economics* 119, 1555-1585.

Paravisini, D., 2008, "Local Bank Financial Constraints and Firm Access to External Finance," *Journal of Finance 63*, 2161-2193.

Peek, J., Rosengren, E, 1997, "The International Transmission of Financial Shocks: The Case of Japan," *American Economic Review* 87, 495-505.

Petersen, M. A., and Rajan, R. G., 2002, "Does Distance Still Matter? The Information Revolution in Small Business Lending," *Journal of Finance* 57, 2533-2570.

Plosser, M., 2011, "Bank Heterogeneity and Capital Allocation: Evidence from 'Fracking' Shocks," Working Paper.

Rice, T., Strahan, P. E., 2010, "Does Credit Competition Affect Small-Firm Finance," *Journal of Finance* 65, 861-889.

Schnabl, P., 2012, "The International Transmission of Bank Liquidity Shocks: Evidence from an Emerging Market," *Journal of Finance* 67, 897-932.

Stein, J. C., 1998, "An Adverse Selection Model of Bank Asset and Liability Management with Implications for the Transmission of Monetary Policy," *RAND Journal of Economics* 29, 466-486.

Stiroh, K. J., Strahan, P. E., 2003, "Competitive Dynamics and Competition: Evidence from U.S. Banking," *Journal of Money, Credit, and Banking* 35, 801-828.

Times-Picayune, 2008, "SWEET SPOT; A Recent Rush on Natural Gas Drilling in Northwest Louisiana is Turning Many Landowners into Instant Millionaires, and Stoking Others' Hopes," September 17.

Yergin, D., 2011 "The Quest: Energy, Security, and the Remaking of the Modern World," The Penguin Press.

Figure 1: Location of Shale Activity

The figure maps the counties of the 7 shale boom states included in this study: AR, LA, ND, OK, PA, TX and WV. White counties are non-boom counties while shaded counties are shale boom counties as of 2010.

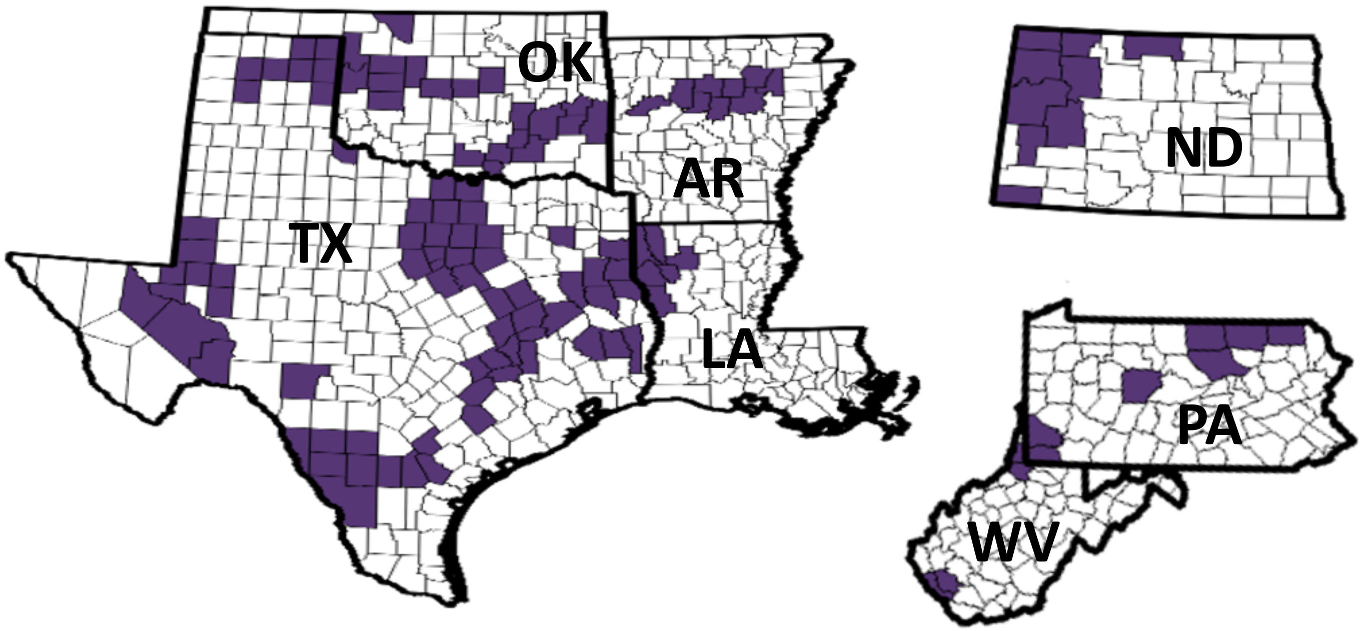

Figure 2: Securitization and Sold Rates, Local vs. Distant Loans

This figure plots the fraction of loans that are securitized or sold for local versus distant loans over the sample period in our study. A local loan is defined as a loan made in the same county in which a bank has a branch, while a distant loan is a loan made in a county by a lender that does not have a branch.

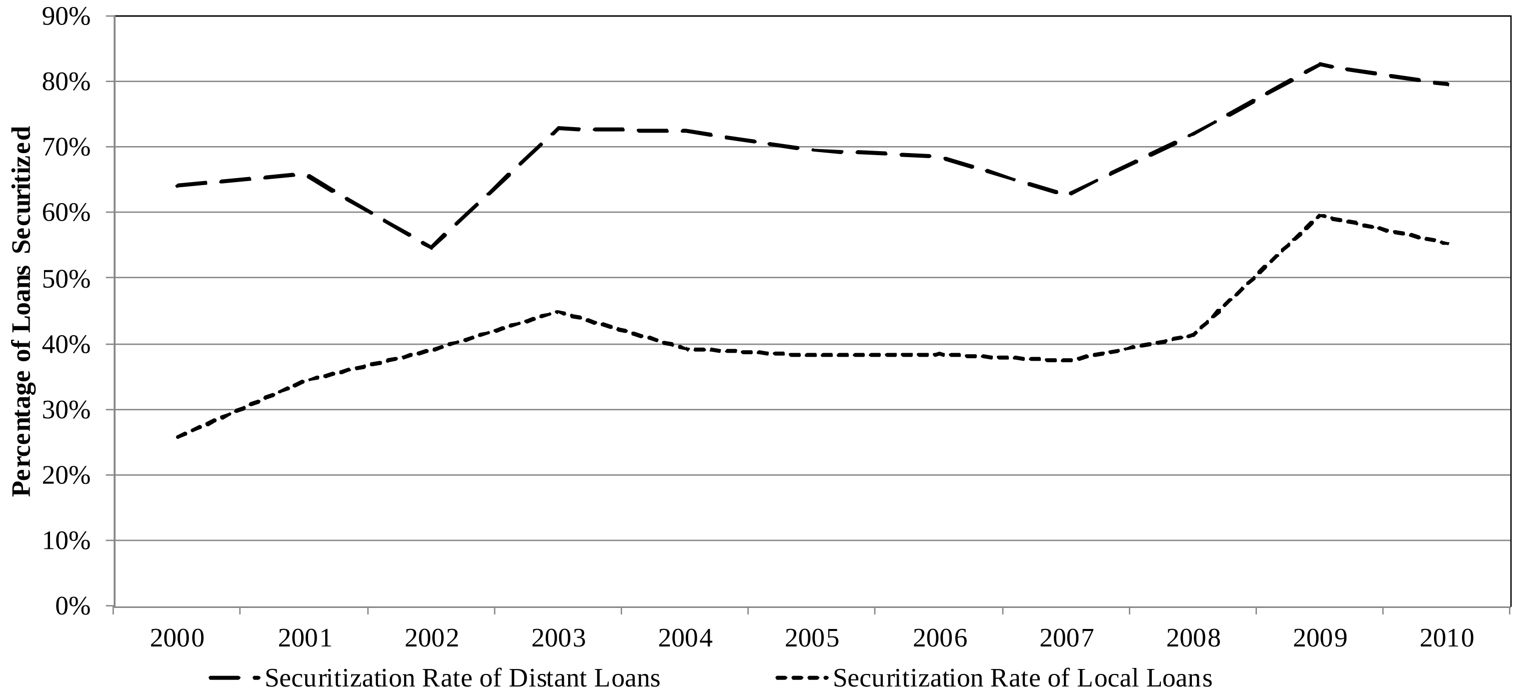

Table 1: Summary Statistics

This table reports summary statistics for banks operating in states with counties exposed to the shale boom. The unit of observation is bank-year in Panel A and Panel B, and bank-county-year in Panel C. The sample is built from the 7 states that experienced shale booms between 2000 and 2010. *Share of Branches in Boom Counties* equals the fraction of a bank's branches located in shale-boom counties (variable set to 0 before the onset of a shale boom). *Growth in Shale Well Exposure* equals the weighted exposure to the growth in the number of shale wells where the fraction of a bank's branches in boom counties serve as weights. The distribution of bank branches comes from the FDIC *Summary of Deposits*, which we use to determine whether or not a branch (or the bank that owns it) is or is not exposed to the boom. Bank characteristics come from year-end *Call Reports*. Growth in mortgage originations comes from the annual *HMDA* data.

	Non-Exposed Banks		Exposed Banks	
	Mean	Std. Deviation	Mean	Std. Deviation
Panel A: Exposure to Deposit Shock				
Share of Branches in Boom Counties	0	0	0.45	0.39
Growth in Shale Well Exposure	0	0	0.25	0.51
Number of Bank-Years	7,451		1,280	
Panel B: Bank Characteristics				
Deposit Growth	0.085	0.141	0.102	0.156
Log of Assets	12.451	1.390	13.428	2.090
Deposits / Assets	0.827	0.086	0.827	0.087
Cost of Deposits	0.022	0.010	0.017	0.008
Liquid Assets / Assets	0.273	0.148	0.225	0.132
Capital / Assets	0.099	0.028	0.101	0.029
C&I Loans / Asset	0.112	0.090	0.145	0.087
Mortgage Loans / Assets	0.347	0.137	0.323	0.117
Net Income / Assets	0.009	0.008	0.008	0.011
Loan Commitments / Assets	0.109	0.140	0.134	0.182
Letters of Credits / Assets	0.006	0.011	0.010	0.020
Panel C: Annual Mortgage Growth Rates				
Growth in Mortgage Originations	0.112	0.621	0.117	0.576
Growth in Retained Mortgages	0.077	0.672	0.091	0.618

Table 2: Effect of Deposit Supply Shock on Mortgage Lending

This table compares OLS and IV regressions of the percentage change in mortgage originations by bank-county-year. The sample is built from bank-county-years in the 7 states that experienced shale booms between 2000 and 2010. Bank-county-years are excluded if the county actually experienced a shale-boom. *Share of Branches in Boom Counties* equals the fraction of a bank's branches located in shale-boom counties (variable set to 0 before the onset of a shale boom). *Mortgage Growth* equals the percentage change in originations from the prior year; *Retained Growth* equals the percentage change in mortgages held on the lender's balance sheet; *Sold Growth* equals the percentage change in mortgages sold by the originator. Regressions include both lender (reported) and borrower (not reported) control variables. Lender controls are from the Call Reports from the prior year; borrower controls are the average borrower and area income, loan size-to-income ratio, percent women and percent minority and percent minority in the area for loans made during the current year (from HMDA). Standard errors are clustered by bank. All regressions also include county*year fixed effects.

Dependent Variable	First-Stage Deposit Growth$_t$		Mortgage Growth		Retained Growth		Sold Growth	
			OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of Branches in Boom Counties$_t$	0.156**	-	-	-	-	-	-	-
	(1.97)	-	-	-	-	-	-	-
Growth in Shale Well Exposure$_t$	-	0.127***	-	-	-	-	-	-
	-	(3.10)	-	-	-	-	-	-
Deposit Growth$_t$	-	-	0.637***	0.936*	0.575***	2.269***	0.434***	0.647
	-	-	(5.37)	(1.77)	(3.92)	(3.52)	(4.35)	(1.18)
Log of Assets$_{t-1}$	0.00294	0.00213	-0.0139	-0.0148*	-0.0123	-0.0207*	-0.0238**	-0.0252***
	(0.71)	(0.54)	(1.63)	(1.76)	(1.38)	(1.87)	(2.53)	(2.94)
Deposits / Assets$_{t-1}$	-0.154	-0.139*	0.0245	0.0728	-0.261	-0.0931	0.114	0.16
	(1.64)	(1.67)	(0.15)	(0.37)	(1.24)	(0.33)	(0.60)	(0.79)
Cost of Deposits$_{t-1}$	-3.324	-3.377	0.805	1.838	-0.287	1.372	-4.257	-2.618
	(1.56)	(1.59)	(0.35)	(0.67)	(0.09)	(0.41)	(1.01)	(0.64)
Liquid Assets / Assets$_{t-1}$	0.0879	0.0692	0.0963	0.0685	-0.0819	-0.183	0.392**	0.312
	(0.75)	(0.69)	(0.69)	(0.48)	(0.43)	(0.59)	(2.18)	(1.59)
Capital / Assets$_{t-1}$	0.0272	0.0814	-1.471**	-1.467*	-0.3	-0.263	-2.118***	-2.158***
	(0.08)	(0.24)	(2.00)	(1.89)	(0.43)	(0.25)	(2.99)	(3.00)
C&I Loans / Asset$_{t-1}$	0.273***	0.264***	-0.0873	-0.175	-0.137	-0.483	0.118	0.0259
	(3.60)	(3.50)	(0.58)	(0.78)	(0.50)	(1.58)	(0.42)	(0.08)
Mortgage Loans / Assets$_{t-1}$	0.167	0.12	-0.0567	-0.112	-0.0648	-0.279	0.192	0.0985
	(1.19)	(1.18)	(0.35)	(0.63)	(0.32)	(0.85)	(1.19)	(0.46)
Net Income / Assets$_{t-1}$	1.027	1.104	3.822**	3.48	6.419*	8.175*	2.35	2.225
	(0.66)	(0.75)	(2.01)	(1.55)	(1.82)	(1.73)	(0.87)	(0.97)
Loan Commitments / Assets$_{t-1}$	0.0205	0.0186	0.0171	0.0109	-0.0286	-0.0559	0.009	0.000886
	(1.46)	(1.43)	(0.71)	(0.38)	(0.74)	(1.09)	(0.27)	(0.03)
Letters of Credits / Assets$_{t-1}$	-0.289	-0.227	0.942	1.058	0.488	1.2	2.608**	2.768***
	(0.83)	(0.66)	(1.14)	(1.29)	(0.62)	(1.47)	(2.43)	(2.66)
Borrower Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Clustered St Errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	92,144	92,144	92,144	92,069	71,034	70,910	49,427	49,221
R-squared	9.9%	11.6%	2.8%		2.2%		2.4%	

*T-stats reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.*

Table 3: Determinants of Entrance and Exit Decisions and Shale Booms

This table estimates regressions of the determinants of a bank's shale boom exposure. The unit of observation is bank-year, and the dependent variable is a bank's shale boom exposure. *Exposure Based on 2002 Branch Distribution* is a bank's shale boom exposure based on holding its branch structure as of 2002. Application volume growth equals the percentage change in applications from the prior year, one and two year lags of this variable are included in the specifications. Columns (4) through (6) also include bank fixed effects, year fixed effects, and lender-specific control variables based on prior year call reports. Application Volume Growth measures are based on HMDA. Standard errors are clustered by bank.

Panel A

Dependent Variable	Share of Branches in Boom Counties					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure Based on 2002 Branch Distribution	0.941***	0.945***	0.945***	0.912***	0.909***	0.909***
	(92.47)	(91.77)	(91.40)	(53.00)	(50.88)	(50.97)
Application Volume Growth$_{t-1}$	0.0002	-	0.0001	-0.0002	-	-0.001
	(0.34)	-	(0.02)	(0.26)	-	(0.65)
Application Volume Growth$_{t-2}$	-	0.001	0.001	-	0.001	0.001
	-	(1.64)	(1.33)	-	(1.09)	(0.71)
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank Financial Controls	-	-	-	Yes	Yes	Yes
Bank Effects	-	-	-	Yes	Yes	Yes
Observations	9,049	8,482	8,322	7,549	7,065	6,948
R-squared	92.5%	93.1%	93.2%	96.7%	96.8%	96.9%

Panel B

Dependent Variable	Growth in Shale Well Exposure					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure Based on 2002 Branch Distribution	0.961***	0.962***	0.961***	0.942***	0.941***	0.940***
	(88.87)	(87.78)	(86.94)	(57.76)	(57.30)	(57.05)
Application Volume Growth$_{t-1}$	-0.001	-	-0.001	-0.001	-	-0.002
	(0.54)	-	(0.70)	(0.57)	-	(0.95)
Application Volume Growth$_{t-2}$	-	0.0016*	0.001	-	0.002	0.001
	-	(1.83)	(1.24)	-	(1.30)	(0.61)
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank Financial Controls	-	-	-	Yes	Yes	Yes
Bank Effects	-	-	-	Yes	Yes	Yes
Observations	9,049	8,482	8,322	7,549	7,065	6,948
R-squared	93.7%	93.9%	94.0%	96.8%	97.0%	97.1%

*T-stats reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.*

Table 4: Effect of Deposit Supply Shock on Mortgage Lending: Reduced Form Regressions

This table reports reduced form regressions of the percentage change in mortgage originations by bank-county-year on measures of the exposure to shale-boom counties. Bank-county-years are excluded if the county actually experienced a shale boom. *Mortgage Growth* equals the percentage change in originations from the prior year; *Retained Growth* equals the percentage change in mortgages held on the lender's balance sheet; *Sold Growth* equals the percentage change in mortgages sold by the originator. Regressions include both lender (reported) and borrower (not reported) control variables. Lender controls are from the Call Reports from the prior year; borrower controls are the average borrower and area income, loan size-to-income ratio, percent women and percent minority and percent minority in the area for loans made during the current year (from HMDA). Standard errors are clustered by bank. All regressions also include county*year fixed effects.

Dependent Variable	Mortgage Growth		Retained Growth		Sold Growth	
	(1)	(2)	(3)	(4)	(5)	(6)
Share of Branches in Boom Counties$_t$	0.146**	-	0.325**	-	0.202	-
	(2.17)	-	(2.26)	-	(1.26)	-
Growth in Shale Well Exposure$_t$	-	0.0533**	-	0.223***	-	0.0674
	-	(1.97)	-	(2.69)	-	(1.37)
Log of Assets$_{t-1}$	-0.0121	-0.0124	-0.0096	-0.0107	-0.0217**	-0.0224**
	(1.45)	(1.49)	(1.11)	(1.27)	(2.10)	(2.15)
Deposits / Assets$_{t-1}$	(0.07)	(0.07)	(0.31)	(0.29)	0.06	0.07
	(0.41)	(0.39)	(1.40)	(1.32)	(0.31)	(0.33)
Cost of Deposits$_{t-1}$	(1.27)	(1.31)	(0.88)	(0.96)	(6.30)	(6.43)
	(0.43)	(0.44)	(0.24)	(0.27)	(1.37)	(1.39)
Liquid Assets / Assets$_{t-1}$	0.151	0.144	-0.0596	-0.0864	0.497**	0.486**
	(1.08)	(1.03)	(0.31)	(0.45)	(2.58)	(2.53)
Capital / Assets$_{t-1}$	-1.442**	-1.439**	-0.243	-0.173	-1.987***	-1.990***
	(2.20)	(2.20)	(0.39)	(0.28)	(2.92)	(2.94)
C&I Loans / Asset$_{t-1}$	0.081	0.0829	-0.0453	-0.0575	0.214	0.222
	(0.54)	(0.55)	(0.16)	(0.20)	(0.70)	(0.73)
Mortgage Loans / Assets$_{t-1}$	0.0445	0.031	-0.0104	-0.0697	0.289*	0.269
	(0.29)	(0.20)	(0.05)	(0.33)	(1.73)	(1.54)
Net Income / Assets$_{t-1}$	4.441**	4.517**	5.606*	5.764*	2.474	2.593
	(2.29)	(2.33)	(1.76)	(1.78)	(0.76)	(0.80)
Loan Commitments / Assets$_{t-1}$	0.0301	0.0292	-0.0191	-0.0222	0.0218	0.0194
	(1.32)	(1.28)	(0.51)	(0.59)	(0.57)	(0.51)
Letters of Credits / Assets$_{t-1}$	0.787	0.768	0.402	0.452	2.525**	2.497**
	(0.94)	(0.92)	(0.47)	(0.53)	(2.25)	(2.23)
Borrower Controls	Yes	Yes	Yes	Yes	Yes	Yes
County*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank Clustered St Errors	Yes	Yes	Yes	Yes	Yes	Yes
Observations	92,144	92,144	71,034	71,034	49,427	49,427
R-squared	7.3%	7.3%	7.9%	8.0%	13.0%	13.0%

*T-stats reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.*

Table 5: Reduced Form Robustness Tests

This table estimates reduced form regressions of the percentage change in mortgage originations by bank-county-year using different robustness specifications. Bank-county-years are excluded if a county actually experienced a shale boom. *Mortgage Growth* equals the percentage change in originations from the prior year. Regressions include both lender (not reported) and borrower (not reported) control variables. Lender controls are from the Call Reports from the prior year; borrower controls are from HMDA. Columns (1) and (2) report the analysis of parallel trends of exposed and non-exposed banks. The Pre-Boom Indicator for Booming Banks is equal to 1 for booming banks in all the years leading to the boom exposure and zero otherwise. The indicator is always equal to zero for banks that have never been exposed to the boom. Columns (3) and (4) report results based on counties that do not border any of the boom counties. In columns (5) and (6) we eliminate banks with negligible exposure to the boom, those with less than 2.5% of affected branches. Columns (7) and (8) report results based on bank-county-years where lender originated at least 15 mortgages in two subsequent years. Finally, in columns (9) and (10) we incorporate bank*county fixed effects. All regressions also include county-year fixed effects.

	Dependent Variable: Mortgage Growth									
	Parallel Trend Tests		Excluding Counties Neighboring Boom Counties		Drop Banks with <2.5% Exposure to the Boom		Bank-County observations with at Least 15 Mortgages		Bank*County Fixed Effects	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Share of Branches in Boom Counties	0.177**	-	0.183**	-	0.172**	-	0.230***	-	0.273***	-
	(2.18)	-	(2.17)	-	(2.50)	-	(3.22)	-	(5.89)	-
Growth in Shale Well Exposure	-	0.0535*	-	0.061***	-	0.0622**	-	0.0616**	-	0.110***
	-	(1.87)	-	(2.00)	-	(1.98)	-	(2.32)	-	(6.55)
Pre-Boom Indicator for Booming Banks	0.014	0.014	-	-	-	-	-	-	-	-
	(0.38)	(0.36)	-	-	-	-	-	-	-	-
Borrower & Lender Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County*Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Clustered St Errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank*County Fixed Effects	-	-	-	-	-	-	-	-	Yes	Yes
Observations	92,144	92,144	62,189	62,189	81,788	81,788	30,365	30,365	92,144	92,144
R-squared	7.3%	7.3%	7.0%	7.1%	7.6%	7.6%	19.7%	19.7%	16.5%	16.5%

*T-stats reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.*

Table 6: Deposit Supply Shock and Mortgage Lending: The Effect of Local Lenders

This table reports reduced form regressions of the percentage change in mortgage originations by bank-county-year. Bank-county-years are excluded if the county actually experienced a shale boom. *Local Lenders* are those with a branch in the county (distant lenders originate mortgages without a branch in the county). *Mortgage Growth* equals the percentage change in originations from the prior year. Regressions include both lender (reported) and borrower (not reported) control variables. Lender controls are from the Call Reports from the prior year; borrower controls are the average borrower and area income, loan size-to-income ratio, percent women and percent minority and percent minority in the area for loans made during the current year (from HMDA). Standard errors are clustered by bank. All regressions also include county*year fixed effects.

Dependent Variable	Mortgage Growth			
	All Lenders		Local Lenders Only	
	(1)	(2)	(3)	(4)
Local-Lender Indicator	0.008	0.008	-	-
	(0.48)	(0.54)	-	-
Share of Branches in Boom Counties	0.100	-	0.234**	
	(1.30)	-	(2.35)	
Growth in Shale Well Exposure	-	0.035	-	0.103**
	-	(1.00)	-	(2.03)
Share of Branches in Boom Counties *	0.231**	-	-	-
Local-Lender Indicator	(2.17)	-	-	-
Growth in Shale Well Exposure	-	0.126**	-	-
Local-Lender Indicator	-	(1.99)	-	-
Log of Assets$_{t-1}$	-0.012	-0.012	0.009	0.009
	(1.52)	(1.54)	(1.03)	(1.05)
Deposits / Assets$_{t-1}$	-0.124	-0.121	0.404***	0.402***
	(0.69)	(0.66)	(3.91)	(3.90)
Cost of Deposits$_{t-1}$	-2.552	-2.555	-1.360	-1.360
	(0.85)	(0.85)	(0.25)	(0.25)
Liquid Assets / Assets$_{t-1}$	0.116	0.112	0.260**	0.261**
	(0.80)	(0.78)	(2.19)	(2.19)
Capital / Assets$_{t-1}$	-1.432**	-1.431**	-0.320	-0.318
	(2.15)	(2.15)	(0.50)	(0.49)
C&I Loans / Asset$_{t-1}$	0.019	0.022	0.185	0.190
	(0.12)	(0.14)	(1.16)	(1.19)
Mortgage Loans / Assets$_{t-1}$	0.085	0.077	0.053	0.050
	(0.56)	(0.49)	(0.34)	(0.32)
Net Income / Assets$_{t-1}$	3.872*	3.938*	2.103	2.155
	(1.85)	(1.87)	(0.82)	(0.84)
Loan Commitments / Assets$_{t-1}$	0.026	0.025	-0.101	-0.103
	(1.16)	(1.13)	(0.73)	(0.75)
Letters of Credits / Assets$_{t-1}$	0.654	0.628	-0.261	-0.304
	(0.75)	(0.72)	(0.38)	(0.44)
Borrower Controls	Yes	Yes	Yes	Yes
County*Year FE	Yes	Yes	Yes	Yes
Bank Clustered St Errors	Yes	Yes	Yes	Yes
Observations	93,739	93,739	22,316	22,316
R-squared	7.3%	7.2%	20.2%	20.2%

*T-stats reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.*

Table 7: Effect of Deposit Supply Shock by Mortgage Type

This table reports reduced form regressions of the percentage change in mortgage originations by bank-county-year, broken out by mortgages for home purchase, home-equity lines, and refinancing. Bank-county-years are excluded if the county actually experienced a shale boom. Regressions include both lender and borrower control variables (not reported). Lender controls are from the Call Reports from the prior year; borrower controls are the average borrower and area income, loan size-to-income ratio, percent women and percent minority and percent minority in the area for loans made during the current year (from HMDA). Standard errors are clustered by bank. All regressions also include county*year fixed effects.

Dependent Variable	*Mortgage Growth*		
	Home Purchase Mortgages	Home Equity Loans	Refinancings
	(1)	(2)	(3)
Panel A			
Local-Lender Indicator	-0.0350**	-0.0372	-0.00673
	(-2.554)	(-1.206)	(-0.338)
Share of Branches in Boom Counties	0.0626	-0.172	0.188*
	(0.89)	(-0.978)	(1.91)
Share of Branches in Boom Counties *	0.245**	0.592***	0.0642
Local-Lender Indicator	(2.44)	(2.74)	(0.50)
Borrower & Lender controls	Yes	Yes	Yes
County*Year FE	Yes	Yes	Yes
Bank Clustered St Errors	Yes	Yes	Yes
Observations	64,860	34,839	66,237
R^2	9%	16%	15%
z-statistic for: (1)==(2)		(1.457)	
z-statistic for: (2)==(3)		(2.099)	
z-statistic for: (1)==(3)		(1.106)	
Panel B			
Local-Lender indicator	-0.0348**	-0.0345	-0.00692
	(-2.564)	(-1.140)	(-0.355)
Growth in Shale Well Exposure	0.034	-0.083	0.0483
	(1.07)	(-1.533)	(1.16)
Growth in Shale Well Exposure *	0.154**	0.305***	0.0328
Local-Lender Indicator	(2.33)	(2.87)	(0.45)
Borrower & Lender controls	Yes	Yes	Yes
County*Year FE	Yes	Yes	Yes
Bank Clustered St Errors	Yes	Yes	Yes
Observations	64,860	34,839	66,237
R^2	9%	16%	15%
z-statistic for: (1)==(2)		(1.208)	
z-statistic for: (2)==(3)		(2.108)	
z-statistic for: (1)==(3)		(1.227)	

*T-stats reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.*

Table 8: Effect of Deposit Supply Shock on Mortgage Lending:
All Counties for Local Lenders Only

This table reports reduced form regressions of the percentage change in mortgage originations by bank-county-year. In this table, we include bank-county-years for counties that actually experienced shale booms in columns (1) and (2). Columns (3) and (4) include only non-boom counties; these repeat the results from Table 6 and are included to ease comparison across samples. *Mortgage Growth* equals the percentage change in originations from the prior year. Regressions include both lender (reported) and borrower (not reported) control variables. Lender controls are from the Call Reports from the prior year; borrower controls are the average borrower and area income, loan size-to-income ratio, percent women and percent minority and percent minority in the area for loans made during the current year (from HMDA). Standard errors are clustered by bank. All regressions also include county*year fixed effects.

Dependent Variable	Mortgage Growth			
	All Counties		Non-Boom Only	
	(1)	(2)	(3)	(4)
Boom-County Indicator	Coefficient absorbed by the county*year fixed effects			
Share of Branches in Boom Counties	0.286***	-	0.234**	-
	(2.81)	-	(2.35)	-
Growth in Shale Well Exposure	-	0.118**	-	0.103**
	-	(2.28)	-	(2.03)
Share of Branches in Boom Counties *	-0.272**	-	-	-
Boom-County Indicator	(2.52)	-	-	-
Growth in Shale Well Exposure	-	-0.11**	-	-
Boom-County Indicator	-	(1.98)	-	-
Log of Assets	0.00922	0.00939	0.009	0.009
	(1.20)	(1.21)	(1.03)	(1.05)
Deposits / Assets$_{t-1}$	0.390***	0.388***	0.404***	0.402***
	(3.92)	(3.90)	(3.91)	(3.90)
Cost of Deposits$_{t-1}$	-0.818	-0.827	-1.360	-1.360
	(0.16)	(0.16)	(0.25)	(0.25)
Liquid Assets / Assets$_{t-1}$	0.343***	0.343***	0.260**	0.261**
	(2.95)	(2.94)	(2.19)	(2.19)
Capital / Assets$_{t-1}$	-0.21	-0.208	-0.320	-0.318
	(0.33)	(0.32)	(0.50)	(0.49)
C&I Loans / Asset$_{t-1}$	0.248	0.255*	0.185	0.190
	(1.63)	(1.67)	(1.16)	(1.19)
Mortgage Loans / Assets$_{t-1}$	0.114	0.111	0.053	0.050
	(0.77)	(0.74)	(0.34)	(0.32)
Net Income / Assets$_{t-1}$	1.987	2.043	2.103	2.155
	(0.83)	(0.85)	(0.82)	(0.84)
Loan Commitments / Assets$_{t-1}$	-0.117	-0.119	-0.101	-0.103
	(1.11)	(1.13)	(0.73)	(0.75)
Letters of Credits / Assets$_{t-1}$	-0.0932	-0.141	-0.261	-0.304
	(0.14)	(0.22)	(0.38)	(0.44)
Borrower Controls	Yes	Yes	Yes	Yes
County*Year FE	Yes	Yes	Yes	Yes
Bank Clustered St Errors	Yes	Yes	Yes	Yes
Observations	27,217	27,217	22,329	22,329
R-squared	0.196	0.196	0.202	0.201

*T-stats reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.*

Table 9: Effect of Deposit Supply Shock on Mortgage Lending:
Unserved Credit Demand and Financial Constraints

This table reports reduced form regressions of the percentage change in mortgage originations by bank-county-year. This table includes only lenders with a branch in a given county. Bank-county-years are excluded if the county actually experienced a shale boom. *Lagged Mortgage Approval Rate* equals the bank's approval rate for mortgages made from the prior county-year. *Mortgage Growth* equals the percentage change in originations from the prior year; *Lagged Bank Capital Ratio* equals the book value of capital / total assets for the lender from the prior year. Regressions include both lender and borrower (not reported) control variables. Lender controls are from the Call Reports from the prior year; borrower controls are the average borrower and area income, loan size-to-income ratio, percent women and percent minority and percent minority in the area for loans made during the current year (from HMDA). Standard errors are clustered by bank. All regressions also include county*year fixed effects.

Dependent Variable	Mortgage Growth					
	Share of Branches in Boom County			Growth in Shale Well Exposure		
	(1)	(2)	(3)	(4)	(5)	(6)
Share of Branches in Boom Counties	0.888	-0.176	0.417	-	-	-
	(1.34)	(0.45)	(0.58)	-	-	-
Share of Branches in Boom Counties *	-0.799*		-0.731**	-	-	-
Lagged Mortgage Approval Rate	(1.68)		(2.01)	-	-	-
Share of Branches in Boom County *	-	3.582***	4.132*	-	-	-
Lagged Bank Capital Ratio	-	(2.92)	(1.85)	-	-	-
Growth in Shale Well Exposure	-	-	-	0.423	-0.104	0.155
	-	-	-	(1.17)	(0.49)	(0.46)
Growth in Shale Well Exposure	-	-	-	-0.409*	-	-0.389**
Lagged Mortgage Approval Rate	-	-	-	(1.86)	-	(1.97)
Growth in Shale Well Exposure	-	-	-	-	2.131**	4.61**
Lagged Bank Capital Ratio	-	-	-	-	(1.97)	(2.13)
Lender Controls	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Controls	Yes	Yes	Yes	Yes	Yes	Yes
County*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank Clustered St Errors	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Mortgage Approval Rate & Lagged Bank Capital	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,316	22,316	22,316	22,316	22,316	22,316
R-squared	21.30%	20.20%	21.34%	21.30%	20.20%	21.35%

*T-stats reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.*

Playing the devil's advocate:
The causal effect of risk management on loan quality

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Abstract

Casual observation suggests that most banks do not try to align loan officer incentives with those of the bank (i.e. to grant positive NPV loans). Instead, they deliberately assign opposing incentives to loan officers (loan volume) and risk management (risk). Decisions are then driven by competition of loan officers and risk management trying to defend their particular causes. Using 75,000 retail mortgage applications at a major European bank from 2008-2011, I analyze the effect of risk management involvement on loan default rates. In the period under study, the bank requires risk management approval for loans that are considered risky based on hard information, using a sharp threshold that changes during the sample period. Using a difference-in-difference estimator and a regression discontinuity design, I am able to show that risk management involvement reduces loan default rates by more than 50%. These results add to the understanding of agency conflicts within banks and point to the crucial importance of risk management in resolving internal agency conflicts.

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1. Introduction

A fundamental function of banks is to screen potential borrowers ─ granting loans to "good" borrowers who will pay them back and rejecting loans from "bad" borrowers who won't.[1] Banks hire agents to perform the screening and recent research has pointed out to the crucial role of loan officer incentives for the quality of a banks' screening decisions.[2] While prior research has focused on incentives of a single agent, the loan officer, most banks hire two agents: One is the loan officer, whose primary incentive is to focus on loan volume. The second agent is the risk manager, whose job is to focus on risk. Their different incentives introduces some tension into the loan-making process, but does it result in better outcomes? Surprisingly, the role of risk management in mitigating internal agency problems has caught little attention so far.

This study fills this gap by looking at the impact on loan default rates when risk managers are involved in screening decisions. As is the case with many banks, loan officers at the one I looked at (a major European lending institution) are able to approve certain loan applications on their own. But applications that exceed specified risk thresholds need to be evaluated by the risk department. The risk thresholds the bank has in place includes a hard-information rating (a single "score" factoring in data like credit history and income level) and a loan-to-value (LTV) percentage. I compare loan default rates just below and just above the thresholds using a regression discontinuity design. My findings ─ I analyze 75,000 retail mortgage applications between February 2008 and September 2011

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[1] For a theoretical motivation for this function, see Ramakrishnan and Thakor (1984), Diamond (1984), Allen (1990).

[2] Empirical studies include Agarwal and Ben-David (2013), Berg, Puri, and Rocholl (2013), Cole, Kanz, and Klapper (2013).

— show that the involvement of risk managers in the loan origination process reduces default rates by more than 50 percent.

I address concerns of a manipulation of the rating or LTV – which could invalidate the regression discontinuity design – by tracking loan officer inputs (loan amount, loan and customer characteristics) into the system. Doing so allows me to identify any loan applications where the initial rating-LTV combination would have required risk management involvement, but where the loan officer subsequently changed input parameters in order to avoid that. More formally, I instrument treatment status with the initial input parameters to control for any possible endogenous sorting around the threshold. Estimates from this instrumental variable regression are qualitatively similar and still highly significant.

For purposes of identifying causality, it also helps that the bank, in May of 2009, implemented changes to its threshold for involving the risk management department. Using a difference-in-difference estimator confirms the results from the regression discontinuity design. I also show that the change in default rates is concentrated around May 2009, ruling out any confounding factors that may gradually and differentially affect default rates between those rating-LTV combinations that became subject to a risk management assessment after the threshold change, and those that didn't.

The theoretical literature offers a variety of predictions about the effect of risk management involvement. One theory – which I call the Efficient Advocacy Hypothesis – says that splitting the responsibility for several tasks among two agents (as opposed to mandating one agent for several tasks) can result in superior decision-making (Holmstrom and Milgrom (1990, 1991), Dewatripont and Tirole (1999)). According to Dewatripont and Tirole, decision-making within organizations can be enhanced by assigning two agents to opposing objectives and allowing them, in effect, to compete. Among the more familiar examples of how this creates efficiency is the judicial system, in which defense attorneys and prosecutors make the strongest possible cases for whomever they're representing. An older example of advocacy is how decisions have been made in Christianity (usually in Catholicism) about who gets elevated to the level of a saint. On one side of the canonization process is the "devil's advocate"; on the other is someone who acts as "God's advocate." A second school of thought is much more skeptical about the value of using monitoring agents. Falk and Kosfeld (2006) conducted experiments that suggest that monitoring agents can add hidden costs, in the sense of other agents reducing their performance if they perceive the monitoring to be a control mechanism. This "Hidden Costs of Control Hypothesis" suggests that risk management, if itself viewed by loan officers as a control device, can have a negative effect on loan performance by reducing loan-officer effort. Finally, empirical evidence has lend support to the notion that people are subject to systematic biases, and make predictions that are generally inferior to predictions made purely on the basis of statistics (Meehl (1954), Tversky and Kahnemann (1974), Dawes, Faust and Meehl (1989)). This "Models are Superior to Experts Hypothesis" therefore suggests that relying on risk managers' judgment, instead of sticking to the results of statistical default models, leads to inferior screening decisions.

My findings show that the involvement of risk managers in the loan origination process reduces default rates by more than 50 percent, and thus lend strong support to the efficient advocacy hypothesis. Furthermore, I do not find any evidence that differences in experience are driving the results (the effect of risk management involvement is independent of loan officer experience). Nor do I find evidence that entrenchment plays a role (the effect of risk management involvement is similar for relationship and non-relationship customers). These results thus point to the crucial importance of risk management in resolving internal agency conflicts.

This study adds to the growing literature on agency problems within banks and the optimal organization design of banks to foster information production (Udell (1989), Stein (2002), Berger et al. (2005), Liberti and Mian (2009), Agarwal (2010), Puri, Rocholl, and Steffen (2011, 2013), Agarwal and Ben-David (2013), Berg, Puri, and Rocholl (2013)). Prior research has stressed the need to provide incentive-compatible contracts to employees in general (Baker, Jensen, and Murphy (1988)) and to loan officers in particular (Baker (2000), Heider and Inderst (2012)). In a one-principal-one-agent framework, high-powered incentives lead to greater screening effort, although the incentives' power is muted by deferred compensation and by the limited liability of loan officers (Cole, Kanz, and Clapper (2013)). In practice, the standard approach followed by most banks is to engage a monitor (the risk manager) to control the actions of the agent (the loan officer). It is exactly this risk management involvement that I analyze in this paper. While the role of monitoring other agents is well established in the theoretical literature on contract theory (Alchiam and Demsetz (1972), Holmstrom (1982), Rahman (2012)), there is surprisingly little empirical literature on the agency role of risk management in monitoring loan officers. Hertzberg, Liberti, and Paravisini (2010) provide evidence that loan-officer rotation helps to alleviate moral hazard in monitoring borrowers. Moral hazard stems from the fact that loan officers who have covered a borrower in previous years are reluctant to report bad news, as it would reflect poorly on their decision-making ability. In this paper, I look at loan-granting decisions so that any incentive conflicts do not stem from past decisions, but are a direct consequence of the opposing incentives provided to loan officers and risk managers by banks. In a related paper, Brown et. al. (2013) show that loan officers inflate soft information in reaction to internal risk management controls and thus points to possible hidden costs of control. My paper offers a complementary view by providing causal evidence that risk management can significantly reduce default rates.

This paper also relates to the growing literature on risk management in banks. Stulz (2008) provides a typology of risk management failures while Acharya et al. (2009) call for stronger risk-control management as a response to the recent financial crisis. This is supported by Ellul and Yerramilli (2011) and Aebi, Sabato, and Schmid (2012) who found that certain risk management-related corporate governance mechanisms were associated with a better bank performance during the financial crisis of 2007/2008. While these papers provide a macro view on the link between risk governance and bank performance, this paper aims to causally identify the impact on risk management involvement in the loan-granting process and it is, to the best of my knowledge, the first paper to provide such a micro foundation of risk management within banks.

The rest of the paper is organized as follows. Section 2 describes the loan origination process. Section 3 provides descriptive statistics of the data, Section 4 explains my empirical strategy, and Section 5 presents the empirical results. Section 6 concludes.

2. Loan origination process

I start by describing the loan origination process and the incentives of the parties involved in it. A high-level overview about the loan origination process is provides in Figure 1 and Figure 2.

[Figure 1 and 2 here]

The process proceeds along three steps:

1. Step 1 (Information collection): The loan officer collects information from the loan applicants and inputs it into the bank's systems. Data collected

includes information about the loan characteristics, the collateral and information about the loan applicant. For example, the desired amount and maturity of the loan are inputted into the systems, along with the collateral type (house or apartment), the collateral value as well as income, costs, and existing liabilities of the applicant.

2. Step 2 (Hard information filter): Using the data inputted by the loan officer, the bank's systems determine a hard-information rating, ranging from 1 (best rating) to 12 (worst rating), and the loan-to-value ratio (LTV). Loan applications are then classified using the so-called "traffic light approach": Loan applications with good ratings and/or low LTVs can be granted by the loan officer without risk management approval ("green applications"), while loan applications with a poor rating and/or high LTV require risk management approval ("yellow applications"). Loan applications with a very poor rating (less than 1% of all loan applications) are directly rejected ("red applications"). Figure 3 depicts rating-LTV combinations that require risk management approval: During subperiod 1 (February 2008 – April 2009) only loan applications with an LTV > 100% had to be approved by risk management.[3] During subperiod 2 (May 2009 – September 2011) the bank tightened its lending standards and additionally required loan applications with ratings 6-8 (90% < LTVs ≤ 100%) and rating 8 (72% < LTV ≤ 90%) to be approved by risk management. Loan applications with a rating of 9 or worse cannot be accepted.

[3] Loans can have an LTV above 100% if the bank finances taxes (~5% of the value of the house or aparment) and broker fees (3-7% of the value of the house or aparment) in addition to the purchase price of the house/aparment.

[Figure 3 here]

3. Step 3 (Risk management decision): For loan applications that require risk management approval according to step 2, a risk manager reviews the loan application and makes the final accept/reject decision. All risk managers are located in one single city and risk managers do not talk directly to potential borrowers. The risk manager receives an electronic version of all documents (for example, the income statement and the appraisal of the house/apartment) and communication with the loan officer takes place via email and telephone calls. Risk managers are assigned to specific branches of the bank, meaning that a loan officer always communicates with the same risk manager for all loan applications that s/he handles. Thus, while hard information can be easily transmitted and verified, soft-information can be incorporated to the extent that the risk manager trusts a specific loan officer from truly reporting soft information. The risk manager then communicates his/her final decision (accept/reject) to the loan officer, usually within one or two days after the first contact. The decision of the loan officer does not affect the rating, but just the accept/reject decision itself.

Table 2 provides four examples of risk management decisions. In the first example, the risk manager rejects a loan application. The house that the loan applicants want to purchase is old and clearly needs refurbishment. Refurbishment costs have not been considered, nor is it visible that the applicants would be willing or able to do the refurbishment on their own, nor is the income of the applicants sufficient to support any additional costs. The purchase of the house does not seem to be a well thought-out plan. While the loan officer has incentives to "overlook" the costs of refurbishment, the risk manager clearly has incentives to reject this loan application.

[Table 2 here]

If the loan applicant accepts the bank's loan offer, a contract is signed and the loan is disbursed on the loan start date (usually a couple of weeks after the loan is signed). The bank at hand does not securitize its mortgage loans, so all loans remain on the balance sheet of the bank. Our main variable of interest, the default dummy, is a variable equal to 1 if the loan defaults within the first 24 months after the loan start date. A loan is coded as being in default if it is 90 days past due or unlikely to pay and neither the loan officer nor the risk manager has any responsibility in monitoring the borrower after loan origination.

Loan officers are volume-incentivized while risk managers receive a fixed salary. Beyond these monetary incentives, risk management is viewed as being responsible for containing the level of loan defaults. Ex post, excessive defaults are thus not blamed on loan officers, but on a "failure of risk management". Therefore, loan officers and risk managers face detrimental incentives in the spirit of Dewatripont and Tirole (1999): While loan officers tend to stress arguments in favor of granting a loan, risk managers will usually focus on arguments against granting a (risky) loan. Excessive rejections by risk managers are contained by an implicit commitment to accept a certain fraction of loan applications. During our sample period, risk management accepted approximately 80% of all loan applications that required risk management was involved in.

3. Data and descriptive statistics

The data set contains 76,372 retail mortgage loan applications from a major European bank, spanning the time from February 2008 to September 2011. All loan applications in the data set are first lien loans for owner-occupied houses or apartments by either one or two (e.g., husband and wife) applicants. All loans are fixed rate loans with a scheduled amortization scheme.[4] I drop loan applications with a rating of 9 or worse (less than 1% of observations) as these are directly rejected without further consideration.

[Table 3 here]

Table 3 provides descriptive statistics of the sample. In total, the sample contains 76,372 loan applications of which 67,860 (89%) loan applications do not require risk management ("green applications") approval while 8,512 (11%) can only be approved after risk management involvement ("yellow applications"). Loan applications that do not need risk management approval are on average smaller (EUR 116,000 versus 139,000), have a higher expected recovery rate (77% versus 69%), are more frequently collateralized by a house (77% versus 67%). Loan applications from these "green" applications are on average older (44 years versus 38 years), they are more frequently from two applicants (average number of applicants of 1.67 versus 1.43), from relationship applicants (63% versus 41%) and applicants have a higher interest coverage ratio (31% versus 21%), measured as the ratio of (Net income per year – Cost of living per year) to

[4] The bank does not offer variable-rate interest schemes, negative amortization loans or teaser rate loans.

(Loan amount + Preexisting liabilities[5]). These differences are also reflected in the rating and LTV: The mean rating and LTV for "green" loan applications (rating = 3.75, LTV = 70.69%) is lower than the mean for loan applications with risk management involvement (rating = 5.78, LTV = 102.06%).

While 43% of all "green" loan applications result in a loan being granted (implying that 2 out of 5 loan applicants accept the bank's offer or loan applicants apply at 2.5 banks on average), only 28% of "yellow" loan applications result in a loan being granted. This is not surprising giving that risk management will reject loans it considers to be too risky. The default rate for "green" loans is 2.81% and therefore lower than the default rate for "yellow" loans (3.18%).

These differences in loan and customer characteristics between the "green" and the "yellow" sample provide the main challenge in identifying a causal effect of risk management on loan defaults. The key question is: Is the "yellow" default rate of 3.18% high or low relative to the 2.81% default rate for "green" loans *once the differences in loan and customer characteristics have been taken into account*? I will more formally describe the identification strategy in the next section, but provide same basic reference points in the following paragraphs.

Figure 4 plots default rates by rating grade and status (with/without risk management involvement). In each rating class, "green" loans default more frequently than "yellow" loans.

[Figure 4 here]

Table 4 provides default rates by subperiod (February 2008-April 2009) and rating-LTV combination. There is a decisive drop in default rates along three

[5] All loans are first lien mortgages, but preexisting liabilities, such as consumer loans, overdrafts, or student loans can exist.

dimensions: First, for each rating grade, default rates drop significantly when moving from "green" to "yellow" LTV-classes. For example, for rating classes 3 and 4 in subperiod 1, default rates drop from 5.26% to 1.77% when moving from an LTV below to LTVs above 100%. Second, for each LTV-class default rates drop when moving from "green" to "yellow" rating grades. For example, for LTVs between 90% and 100% in subperiod 2, default rates drop from 4.36% to 2.54% when moving from a rating of 5 to a rating of 6. Both observations suggest that loans that are close to the threshold, but narrowly "green", have higher default rates than loans that are narrowly "yellow". These observations are consistent with a dampening effect of risk management involvement on loan defaults.

[Table 4 here]

Third, I compare differences in default rates between subperiod 1 and subperiod 2 for rating/LTV-combinations that were affected by the change in the threshold (ratings 6-8 for LTVs between 90% and 100% and rating 8 for LTVs between 72% and 90%) versus rating/LTV-combinations that were not affected by the change in the threshold. Figure 5 plots the development of default rates for affected (upper-hand picture) and non-affected rating/LTV-combinations (lower-hand picture). It shows a significant downward jump in default rates for rating/LTV-combinations that were not subject to risk management approval before May 2009, but started to be subject to risk management approval after May 2009. There is no similar downward jump in default rates for rating/LTV-combinations that were not affected by the change in the threshold.

[Figure 5 here]

4. Empirical strategy

4.1 Difference-in-Difference

I define the difference-in-difference estimator as

$$Default(0/1) = f\left(\beta_1 \cdot Affected + \beta_2 \cdot Post + \beta_{12} \cdot Post \times Affected + \gamma \cdot X\right) \qquad (1)$$

where *Default(0/1)* is a dummy equal to one if a borrower defaults within 24 months after the loan start date, *f()* is a function such as the identity function (resulting in a linear model) or the logistic function (resulting in a logit model), *Post* is a dummy equal to one for loan applications in or after May 2009, *Affected* is a dummy equal to one for rating/LTV-combinations that were not subject to risk management approval before May 2009, but were subject to risk management approval after May 2009 (ratings 6-8 for LTVs between 90% and 100%, rating 8 for LTVs between 72% and 90%). *Controls* is a set of loan and customer characteristics. As loan characteristics, I control for the size of the loan (measured by the logarithm of the loan amount in EUR), the loan maturity (measured by the logarithm of the maturity in months), a dummy equal to 1 if the loan is collateralized by a house (the dummy is equal to zero if the collateral is an apartment), the age of the customer (measured by the logarithm of the age in years), the number of borrowers (equal to one for loan applications by a single borrower, equal to two by loan applications from two borrowers, e.g. husband and wife), a relationship dummy (equal to one if the customer has a checking account or current loan with the bank), and the interest coverage ratio (measured as the ratio of (Net income per year – Cost of living per year) to (Loan amount + Preexisting liabilities).

The underlying assumption behind a difference-in-difference estimator is that unobservable characteristics that affect the default rate are comparable between affected and non-affected rating/LTV-combinations. A possible violation for this comparability assumption would be if the improvement of the economy has a different impact on default rates of affected and non-affected rating-LTV-combinations. While it is impossible to *prove* that affected and non-affected rating-LTV-combinations are similar with respect to unobservables, I provide two types of analysis to support the claim that the drop in default rates is indeed a causal effect of risk management involvement. First, I test whether affected and non-affected rating/LTV-combinations follow a similar trend in the pre-event period ("parallel trend assumption"). This reduces a possible bias via unobservables to variables that have a different impact on default rates on affected/non-affected rating-LTV-combinations *from or after May 2009 on only*. Second, I apply econometric techniques to show that there is a downward jump – as opposed to a smooth downward trend – in the default rate in May 2009 for the affected rating-LTV combinations. This limits alternative explanations to unobservable factors that a) have a different impact on affected versus non-affected rating-LTV combinations, *and* b) suddenly changed at the same time when rules for risk management involvement were also changed.

4.2 Regression discontinuity design

A regression discontinuity design is a standard technique for causal inference in situations where treatment is determined by a threshold, with observations on one side of the threshold receiving treatment and observations on the other side of the threshold acting as a control group (Thistlewaite and

Campbell (1960), Imbens and Lemieux (2008), Roberts and Whited (2011)). I define the regression discontinuity estimator as

$$\begin{aligned} Default(0/1) = f[\beta_1 \cdot RMI(0/1) + g_1(DifferenceToCutOff) \\ + g_2(DifferenceToCutOff) \cdot RMI(0/1) + \gamma \cdot X] \end{aligned} \qquad (2)$$

where RMI(0/1) is a dummy ("Risk Management Involvement") equal to one risk management approval is required, g_1 and g_2 are polynomials fitted to the right and the left-hand side of the cutoff for risk management involvement. As above, f denotes a link function such as the identity (linear regression) or the logistic function (logistic regression) and X is the same set of loan and customer controls as used in the difference-in-difference estimator. The regression is estimated for a subset of observations than contains a discontinuity, e.g. for all loan applications with an LTV between 90% and 100% in subperiod 2 to estimate the change in default rates at the threshold rating of 5 (see Figure 3 and Table 4).

The regression discontinuity design relies on two key assumptions: First, the assumption that there are not "contaminating" thresholds. If loans with a rating directly above the threshold for risk management involvement perform significantly different than loans directly below the threshold, we can conclude that *something* happens at the threshold. However, if loans below and above the threshold are treated differently in any other respect apart from risk management involvement (i.e. bonus system, pricing, ex-post monitoring, etc.), there is no way to differentiate between these alternative explanations. I thus elaborated at great length with the staff of the bank to ensure that these thresholds are only used to determine risk management involvement and are not used for pricing purposes or in other process designs.

Second, the regression discontinuity design relies on the assumption that loan applications just below and just above the threshold are comparable.

Comparability follows, and does not have to be assumed by the researcher, if the running variable (rating, LTV) cannot be manipulated by the loan officer. There is some evidence in the literature that even hard information is subject to manipulation by delegated monitors (Berg, Puri, and Rocholl (2013)). As a stylized example of the effect of manipulation on causal inference, please consider the following example: If loan officers manipulate the rating or LTV for high-risk loans (because s/he fears rejection by risk management) but not for low-risk loans, then a higher default rate for loans directly above the threshold is a consequence of loan officer behavior, but not a causal effect of risk management involvement. The advantage of the data set at hand is that I am fully able to control for the extent of such manipulation. The data set allows me to track inputs by loan officers from initial inputs to the final inputs used to determine risk management involvement, and I am thus able to directly compare the performance of manipulated and non-manipulated loan applications. More formally, I am able to explicitly take into account a possible manipulation of the running variable by instrumenting treatment status with the initial input parameters inputted into the system by the loan officer.

4.3 Specifying the link function

Throughout the paper, I will mostly rely on a logistic link function f for economic reasons: I expect effects to be multiplicative and not additive. For example, economic conditions improve over time during the sample period. If two rating classes have a default rate of e.g. 10% and 1%, an improvement in the economy is likely to decrease default rates by the same portion (i.e. from 10% to 9% and 1% to 0.9%) as opposed to the same percentage points (i.e. from 10% to 9% and 1% to 0%). Similar arguments apply to risk management involvement, the main inference variable, and other loan and customer controls.

I therefore mainly use a logistic regression and report odds ratios (exponentiated coefficients) together with z-statistics. An odds ratio below one indicates that the variable of interest has a decreasing effect on default rates and vice versa. More formally odds ratios represent the term:

$$\frac{\dfrac{p(x+dx)}{1-p(x+dx)}}{\dfrac{p(x)}{1-p(x)}} \approx \frac{p(x+dx)}{p(x)} \quad \textit{for small } p(x) \qquad (3)$$

The approximation on the right-hand side follows from the fact that default rates are usually small, i.e. 2% or 5% and not 50% or 70%. We can therefore interpret the odds ratios for the covariate *x* as the factor by which default rates decrease/increase if *x* changes by 1 unit. To ensure the robustness of the results, I have also determined marginal effects (using the methodology of Ai and Norton (2003) for interaction terms) and used a linear regression instead of a logistic regression, with very similar results.

5. Empirical results

5.1 Difference-in-Difference analysis

Testing the parallel trend assumption

I start by testing the parallel trend assumption before May 2009. Looking at Figure 5, I observe that default rates are approximately flat before May 2009 for both the affected rating-LTV combinations as well as for the control group of non-affected rating-LTV combinations. I test the parallel trend assumption more formally using a logistic regression. Results are reported in Table 5. Column (1) reports results for the whole sample period before the threshold change (5 quarters from February 2008 to April 2009) and column (2) to (5) subsequently eliminate one quarter to see whether any difference in trends emerges close to May 2009. I find that the time trend is not significantly different from 1 (in terms of odds ratios), and also the treatment group does not show a time trend that deviates from the overall sample.

[Table 5 here]

Difference-in-Difference: Baseline specification

Table 6 provides the results for the baseline difference-in-difference specification. Column (1) provides results for a model that just contains the *Affected*, *After*, and *Affected* x *After* dummy variables. In line with the univariate results from Figure 5, I find that after the change of the threshold for risk management involvement, default rates decrease significantly for the affected loan applications, i.e. for rating-LTV combinations where no risk management involvement was required in subperiod 1, but risk management involvement was required in subperiod 2. The coefficient is not only statistically highly significant, but also economically: The odds ratio is 0.414, suggesting that the odds of defaulting versus not defaulting decreased by almost 60%. The other coefficients are also in line with the descriptive statistics: Affected loans default significantly more frequently than non-affected loans, and default rates decrease significantly after May 2009. Controlling for rating and LTV-classes (column (2)), as well as customer (column (3)) and loan controls (column (4)) and region fixed effects (column (5)) results in very similar coefficients on the interaction term, ranging from an odds ratio of 0.392 (column (3)) to 0.414 (column (1)).

[Table 6 here]

Difference-in-Difference: Establishing a jump in default rates in May 2009

The difference-in-difference estimator relies on a comparison of average default rates of affected and non-affected rating-LTV combinations pre and post the threshold change. Such a specification is vulnerable to different trends between affected and non-affected groups, for example caused by a different sensitivity to an improvement in economic conditions. While there is no evidence for differences in trends pre May 2009 (i.e. before the threshold is changed), there are clearly differences in the default rate *levels* between affected and non-affected rating-LTV classes. I thus provide further robustness tests with the aim of demonstrating that the change in default rates is concentrated around May 2009, i.e. at the onset of treatment. Table 7 reports the results. Column (1) reports results for a subsample restricted to +/- 4 quarters around the change in the threshold for risk management involvement (May 2008 to April 2010). Column (2) introduces separate time trends for the affected and non-affected groups to control for any smooth trend in default rates. Column (3) allows for different time trends pre and post May 2009 for both the affected and the non-affected rating-LTV combinations. Finally, borrowing from the regression discontinuity literature, column (4) fits 3^{rd} order polynomials on either side of May 2009 for both the affected and unaffected rating-LTV combinations. In all these specifications, results are very similar to the results from the standard difference-in-difference estimator used in Table 6.

[Table 7 here]

5.2 Regression discontinuity

While addressing several concerns, the difference-in-difference specification above still allows for an alternative explanation: Any contaminating event in May 2009 (when risk management thresholds were changed) that differentially impacts default rates between affected and non-affected rating-LTV combinations could potentially explain the pattern of default rates. To address this concern, I provide results for a regression discontinuity design. There are several subsamples for which regression discontinuity techniques can be applied (see Table 4):

1. Subsample 1: Subperiod 1, discontinuity at an LTV ratio of 100%.
2. Subsample 2: Subperiod 2, discontinuity at an LTV ratio of 100% for rating grades 1-5.
3. Subsample 3: Subperiod 2, discontinuity at a rating of 7.5 for LTVs between 72% and 90%.
4. Subsample 4: Subperiod 2, discontinuity at a rating of 5.5 for LTVs between 90% and 100%.

In the following I report results for the latter sample.[6] This choice is motivated by three considerations: First, loan applications just below and just above the 100% LTV threshold (the cutoff that the first two subsamples rely on) are likely not comparable: A 100% LTV is a psychological threshold with customers requesting loans above 100% LTV likely being different from customers requesting a 100% LTV loan. Second, LTV can easily be manipulated by (slightly) changing the requested loan amount. Third, the subsample No. 4 is the largest subsample with 14,659 loan applications (of which 6,212 loans were granted), of which 10,936 are above the threshold (rating 1-5) and 3,723 loan

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[6] Results for the other samples are very similar, apart from the third subsample where the number of observations is too low to establish statistical significance.

applications are below the threshold (rating 6-8).[7] Thus, this sample contains almost half of all loan applications with risk management involvement (8,512, see Table 3).

Regression discontinuity: Baseline specification

Figure 6 provides a graphical presentation of the regression discontinuity design. The right-hand graphs provides results for subperiod 2, where the threshold for risk management involvement in the 90% < LTV ≤100% bracket was a rating of 5.5. The left-hand graphs provide results for subperiod 1, where no such threshold existed, for comparison. There is a clear drop in default rates between a rating of 5 and a rating of 6 in subperiod 2, a drop which is absent in subperiod 1 (see Panel A). Panel B shows that there is no drop in any of the control variables, i.e loan and customer characteristics cannot explain the drop in default rates.

[Figure 6 here]

Table 8 reports results of the formal regression, using a logistic regression around a bandwidth of +/-2 notches above and below the threshold rating of 5.5 and a linear trend on either side of the threshold. The bandwidth was determined using the optimal bandwidth selector suggested by McCrary (2008). Results using a linear regression (instead of the logistic regression), using half- or twice the optimal bandwidth and using higher order polynomials (instead of a linear function) are reported in the robustness section.

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[7] As a comparision, the LTV class between 72% and 90% includes just 14,474 loan applications in subperiod 2 (5,681 loans granted) with only 686 loan applications being below the rating threshold of 7.5.

Column (1) reports the baseline specification using only the risk management involvement dummy – which is equal to one for loan applications with a rating of 5.5 or worse – and the linear trends on either side of the threshold. Risk management involvement significantly reduces default rates, with the odds ratio being 0.34 (66 percent reduction in the odds ratio). Using the average default rate of 4.36% for a rating of 5 just above the threshold, this means that risk management involvement reduces default rates by 2.8 percentage points. Results are very similar after introducing control variables (column (2) and (3)) as well as using a linear regression model (column (4)).

[Table 8 here]

Regression discontinuity: Instrumenting treatment status

In column (5), I instrument risk management involvement using the rating-LTV combination from the initial scoring trial. More formally, I use the input parameters from the initial scoring trial to determine an initial rating and LTV. This initial rating-LTV combination is then mapped to treatment status (risk management involvement = yes/no). Given the usual problems of IV estimator in non-linear models, I apply a linear regression model in the first as well as in the second stage. Consistent with loan officer manipulation, the IV-estimator results in slighly lower estimates of the effect of risk management involvement (-2.9% versus -3.3%) after controlling for endogenous sorting around the threshold. The coefficient is, however, still significant, both economically and statistically.

Regression discontinuity: Robustness tests

Table 9 provides further robustness tests using a different bandwidth choice around the threshold for risk management involvement and using higher order polynomials. Column (1) provides results for odds ratios from a logistic regression, column (2) provides marginal effects and column (3) provides results for a linear regression specification. Finally, column (4) uses a loss variable, defined as DefaultDummy(0/1) x (1 - Expected recovery rate) to see whether results still hold after taking into account expected receipts from the sale of collateral. All specifications confirm the previous results of an economically and statistically highly significant reduction in default rates or losses due to risk management involvement.

[Table 9 here]

Economic impact

A reduction of defaults is not an end in itself, rather the banks' aim is not to grant loans with a negative expected NPV. A back-of-the-envelope estimate of the net present value impact of risk management is as follows: A conservative estimate from the results above is a reduction in default rates by 50% due to risk management involvement. On the other hand, the ratio of loans-granted to loan applications is approximately 1/3 lower for loan applications with risk management involvement (28.42%) compared to loan applications without risk management involvement (43.01%, see Table 3, row labelled "loan granted"). If the mean default rate of loans subject to risk management approval is denoted by p, then these numbers suggest that accepted loans have a default rate of p/2 while rejected loans have a default rate of 2p.[8] For the main LTV-class of loans with 90% < LTV ≤ 100% the mean default rate at the threshold for risk management involvement is roughly 5% (see Table 4, Panel B). This implies a default rate of

[8] Please note that $p/2 \cdot 2/3 + 2p \cdot 1/3 = p$.

2.5% for loans granted with risk management approval and a default rate of 15% for loans that are rejected by risk management. Keeping in mind that these are 2-year cumulative default rates, these numbers suggest a projected annual default rate of 7.5% for loan applications that were rejected by risk management, implying that rejected loans would have been very likely negative NPV given average margins of roughly 100bps. These back-of-the-envelope calculations suggest that involving risk management did help in rejected negative NPV loans and thus improved the overall loan granting decision within the bank.

5.3 Ruling out alternative hypothesis

The prior analysis has shown that risk management involvement significantly reduces default rates. While I have stressed the importance of differential incentives, two alternative explanations need to be considered: First, the average risk manager might have more experience than the average loan officer, and thus differences in experience could drive the results. Second, entrenchment could drive the results if loan officers, in the absence of resistance from risk managers, would tend to overlook the risks of their long-term customers in an attempt to keep them happy.

To analyze these alternative explanations, I separately analyze the effect of risk management involvement for experienced and unexperienced loan officers as well as for relationship customers and non relationship customers. I measure experience by the number of loan applications processed over the past 12 months and split the sample at the median into "experienced" and "unexperienced" loan officers.[9] If experience plays a major role, then the effect of risk management

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[9] Results are very similar when using the number of loans instead of the number of loan applications or other time windows (3 months, 6 months, 2 years).

involvement should be larger for less experienced loan officers. Table 10 reports the results.

[Table 10 here]

I do not find any evidence for the experience channel; the effect of risk management involvement is independent of loan officer experience both in a difference-in-difference analysis (column (1)) as well as in the regression discontinuity design (column (3)).

To analyze a potential entrenchment effect, I analyze whether risk management involvement has a differential effect for non relationship customers – where entrenchment should not play a role – and relationship customers, where entrechment might affect the loan granting decision of the loan officer. I do not find any evidence for an entrenchment effect. Coefficents on *Affected x After x Relationship* in the differen-in-difference analysis and on *RiskMgmtInvolvement(0/1) x Relationship* in the regression discontinuity design are larger than one (suggesting the effect of risk management is *smaller* for relationship customers) and statistically insignificant.

6. Conclusion

Volume-incentivized loan officers are unlikely to make arguments against granting a loan, nevertheless, volume-based incentives dominate industry practice in the banking industry. Advocates in court are rarely found to make arguments for a conviction, yet the judicial system works because the other side of the argument is being made by prosecutors. In banks, risk management is responsible to make "the other side of the argument". Does hiring two agents, one responsible for loan volume (loan officers) and one responsible for risk (risk management), help to facilitate efficient screening decisions? In this study, I examine the impact of risk management involvement in the loan granting process on subsequent loan default rates. I thereby use a setting at a major European bank that requires retail mortgage applications to be approved by risk management if the hard-information rating and the loan-to-value (LTV) ratio cross certain thresholds.

Using a regression discontinuity design and a difference-in-difference estimator, I find that risk management involvement reduces default rates by more than 50%. I further show that loans rejected by risk management would likely have been negative NPV loans, suggesting that risk management involvement added value to the bank.

Prior literature has discussed the adverse effect of the widely used volume-based incentives for loan officers. While one solution is to provide loan officers with high-powered incentives based on ex-post default rates, this paper suggests that alternative routes are possible for containing risk. By deliberately assigning opposing incentives to loan officers (loan volume) and risk management (risk), both arguments in favor of granting a loan as well as arguments against it are considered in the loan granting process, leading to better decision making and lower loan default rates.

References

Acharya, V., T. Philippon, M. Richardson, and N. Roubini (2009): "The financial crisis of 2007-2009: Causes and remedies," *Financial Markets, Institutions & Instruments*, *18*(2), 89-137.

Aebi, V., G. Sabato, and M. Schmid (2012): "Risk management, corporate governance, and bank performance in the financial crisis," *Journal of Banking & Finance*, *36*(12), 3213-3226.

Agarwal, S. and I. Ben-David (2012): “Do Loan Officers’ Incentives Lead to Lax Lending Standards?,” Working Paper.

Agarwal, S. and Hauswald, R. (2010): “Authority and Information,” Working Paper.

Ai, C., E.C. Norton (2003): "Interaction terms in logit and probit models," *Economics letters*, *80*(1), 123-129.

Alchian, A. A., and H. Demsetz (1972): "Production, information costs, and economic organization." *The American Economic Review*, *62*(5), 777-795.

Allen, F. (1990): "The market for information and the origin of financial intermediation," *Journal of financial intermediation*, *1*(1), 3-30.

Baker, G. (2000). The use of performance measures in incentive contracting, "*The American Economic Review*," *90*(2), 415-420.

Baker, G. P., Jensen, M. C., and Murphy, K. J. (1988): "Compensation and incentives: Practice vs. theory," *The Journal of Finance*, *43*(3), 593-616.

Berg, T., Puri, M., and Rocholl, J. (2013): "Loan officer incentives and the limits of hard information," NBER Working Paper No. 19051.

Berger, A. N., N. H. Miller, M. A. Petersen, R. G. Rajan, and J. C. Stein (2005): "Does Function Follow Organizational Form? Evidence from Lending Practices of Large and Small Banks," Journal of Financial Economics, 76, 237-269.

Brown, M., M. Schaller, S. Westerfeld, and M. Heusler (2013), "The Hidden Cost of Control – Evidence from Small Business Lending", Working Paper

Cole, S., M. Kanz and L. Klapper (2012): "Incentivizing Calculated Risk Taking: Evidence from a Series of Experiments with Commercial Bank Loan Officers," Harvard Working Paper.

Dawes, R. M., D. Faust, D., and P.E. Meehl (1989): "Clinical versus actuarial judgment," *Science*, *243*(4899), 1668-1674.

Dewatripont, M., and Tirole, J. (1999): "Advocates," *Journal of Political Economy*, *107*(1), 1-39.

Diamond, D. W. (1984): "Financial intermediation and delegated monitoring," *The Review of Economic Studies*, *51*(3), 393-414.

Ellul, A., and V. Yerramilli (2013): "Stronger risk controls, lower risk: Evidence from US bank holding companies," *The Journal of Finance, 68(5), 1757-1803.*

Falk, A. and Michael Kosfeld (2006): "The hidden costs of control," *American Economic Review*, 96(5), 1611-1630.

Heider, F. and Inderst, R. (2012): "Loan Prospecting," *Review of Financial Studies*, 25(8), 2381-2415.

Hertzberg, A., J. M. Liberti, and D. Paravisini (2010): “Information and Incentives Inside a Firm: Evidence from Loan Officer Rotation," Journal of Finance, 65(3), 795-828.

Holmstrom, B. (1982): "Moral hazard in teams," *The Bell Journal of Economics*, 324-340.

Holmström, B. and P. Milgrom, P. (1990): "Regulating trade among agents," *Journal of Institutional and Theoretical*, 146, 85-105.

Holmstrom, B. and P. Milgrom (1991). Multitask principal-agent analyses: Incentive contracts, asset ownership, and job design. *Journal of Law, Economics, and Organization*, *7*, 24-52.

Imbens, G.W. and T. Lemieux (2008): “Regression discontinuity designs,” Journal of Econometrics, 142, 615-635.

Liberti, J. M., and A. R. Mian (2009): “Estimating the Effect of Hierarchies on Information Use," Review of Financial Studies, 22(10), 4057-4090.

McCrary, J. (2008): "Manipulation of the running variable in the regression discontinuity design: A density test," *Journal of Econometrics*, *142*(2), 698-714.

Meehl, P. E. (1954): "Clinical versus statistical prediction: A theoretical analysis and a review of the evidence," University of Minnesota Press.

Puri, M., J. Rocholl, and S. Steffen (2011): "Rules versus Discretion in Bank Lending Decisions," Working Paper.

Puri, M., J. Rocholl, and S. Steffen (2013): "What kinds of bank-client relationships matter in reducing loan defaults and why?," Working Paper.

Rahman, D. (2012): "But who will monitor the monitor?," *The American Economic Review*, *102*(6), 2767-2797.

Ramakrishnan, R. T., and Thakor, A. V. (1984): "Information reliability and a theory of financial intermediation," *The Review of Economic Studies*, *51*(3), 415-432.

Roberts, M.R. and T.M. Whited (2011): “Endogeneity in Empirical Corporate Finance,“ Working Paper.

Stein, J. C. (2002): “Information Production and Capital Allocation: Decentralized versus Hierarchical Firms," Journal of Finance, 57(5), 1891-1922.

Stulz, R. M. (2008): "Risk management failures: What are they and when do they happen?" *Journal of Applied Corporate Finance*, *20*(4), 39-48

Udell, G. F. (1989): “Loan Quality, Commercial Loan Review and Loan Officer Contracting," Journal of Banking & Finance, 13, 367-382.

Thistlewaite, D., and D. Campbell, (1960): “Regression-discontinuity analysis: an alternative to the ex-post facto experiment,” Journal of Educational Psychology, 51, 309-31.

Tversky, A. and Kahneman, D. (1974): "Judgment under uncertainty: Heuristics and biases," *Science*, *185*(4157), 1124-1131.

Figure 1: Loan granting without (Setup 1) and with risk management (Setup 2)

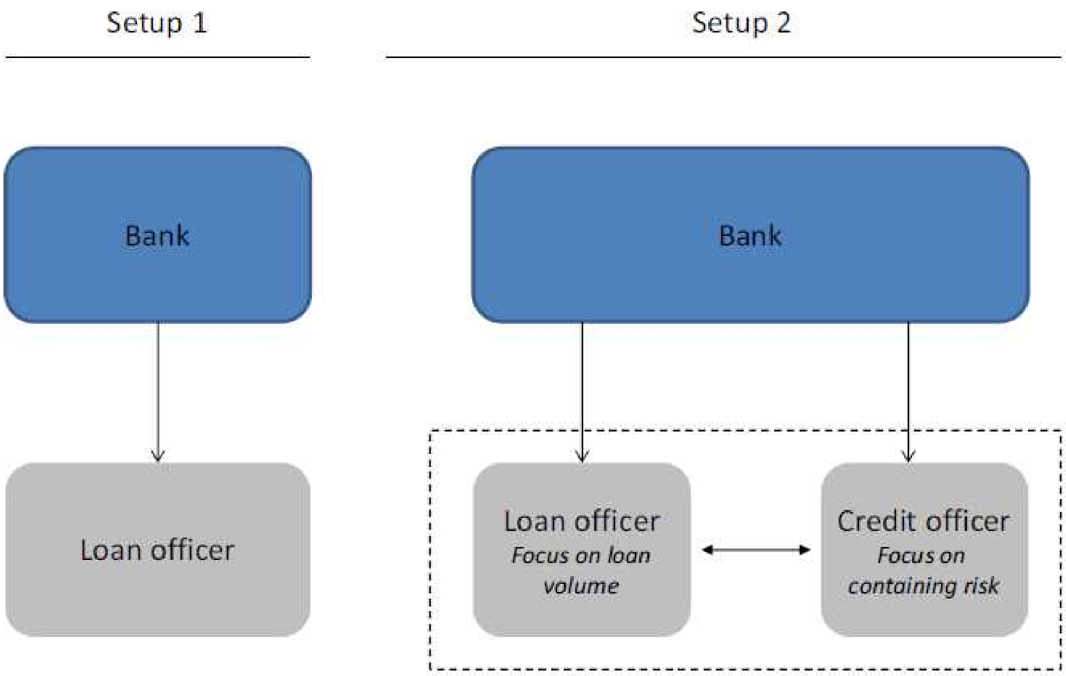
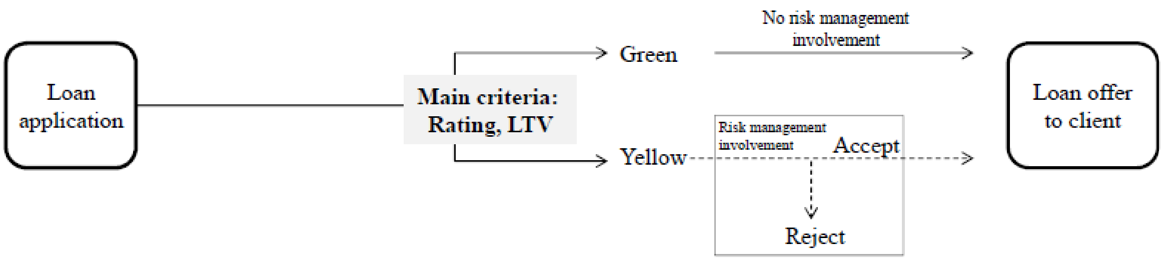


Figure 2: Loan origination process



	Step 1: Information collection	Step 2: Hard information filter	Step 3: Risk management involvement
Tasks	• Client contact • Input application into system	• Sort applications into green (no risk management involvement) and yellow (risk management approval necessary)	• Accept/reject loan application
Responsible	Loan officer	Loan officer (data) Risk mgmt (criteria)	Risk management

Figure 3: Criteria for risk management involvement

This figure depicts the criteria for risk management involvement for both subperiods. The green area, labelled "No risk management involvement", provides the LTV-Rating-combinations where loans can be granted without risk management approval. The yellow area, labelled "Risk management involvement", depicts the LTV-Rating-combinations where risk management approval is necessary to make a loan officer to the loan applicant. Rating denotes the customer's internal rating of the bank, with 1 being the best rating category.

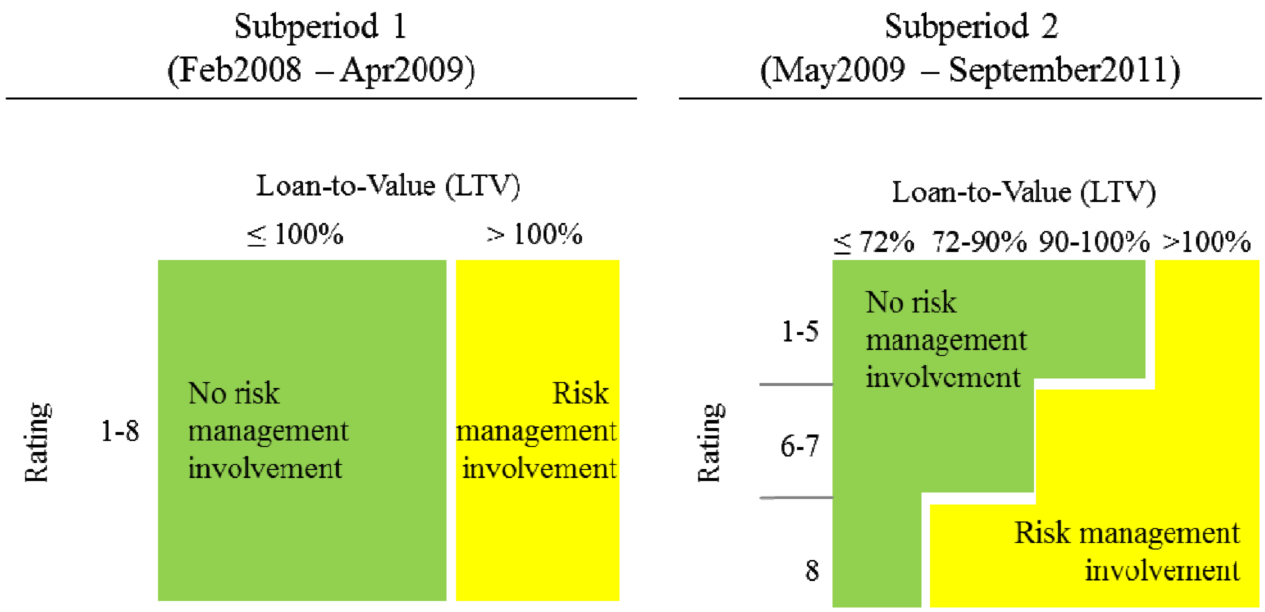


Figure 4: Default rates by process type (with/without risk management involvement)

This figure depicts the default rate over the first 24 months after the loan start date by process type. The dashed green line depicts default rates for loans approved without risk management involvement. The yellow solid line depicts default rates for loans approved with risk management involvement. The grey area depicts one standard error bands around the mean.

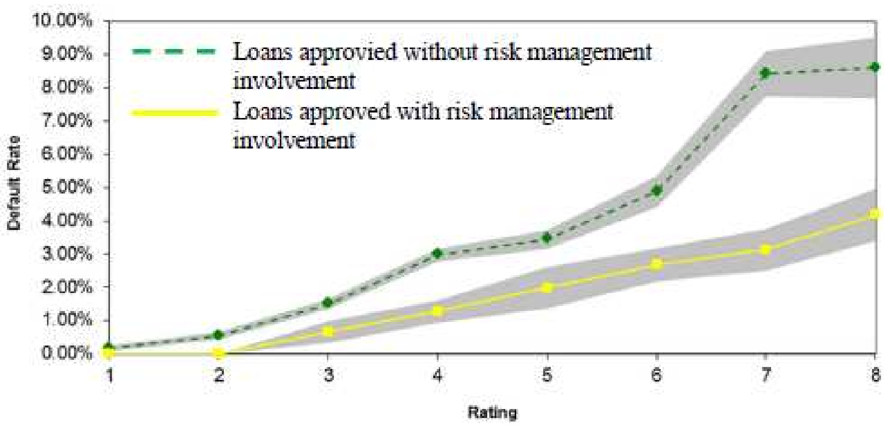
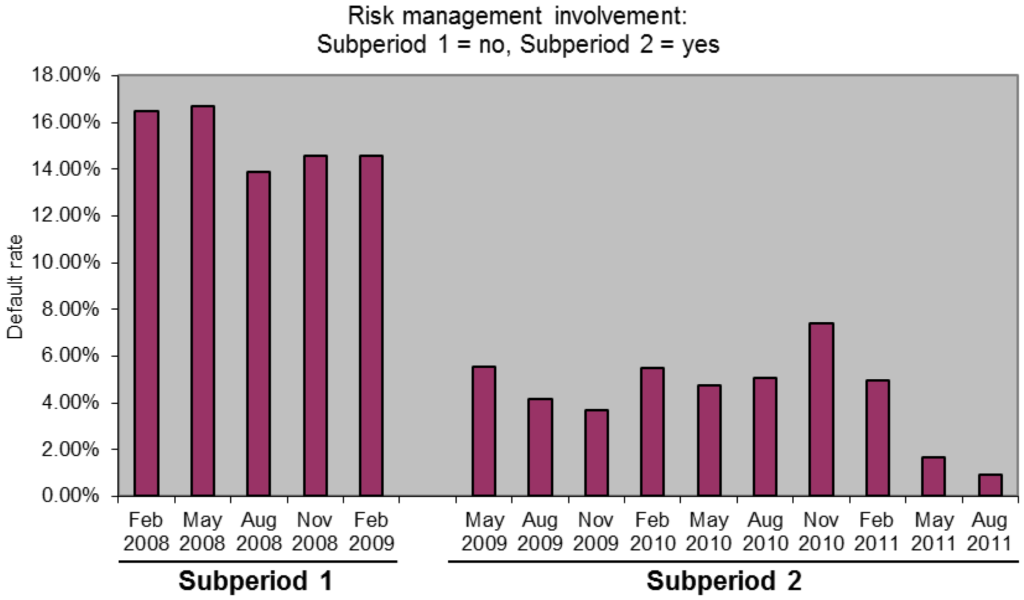


Figure 5: Time series of default rates

This figure depicts default rates over the first 24 months after the loan start date for different subsets of loans. The upper-hand figure presents default rates for rating-LTV combinations where no risk management approval was necessary during the first subperiod (February 2008 – April 2009) and risk management approval was necessary during the second subperiod (May 2009 – September 2011). The lower-hand figure presents default rates for rating-LTV combinations where either no risk management approval was necessary in both subperiods or risk management involvement was necessary in none of the subperiods.



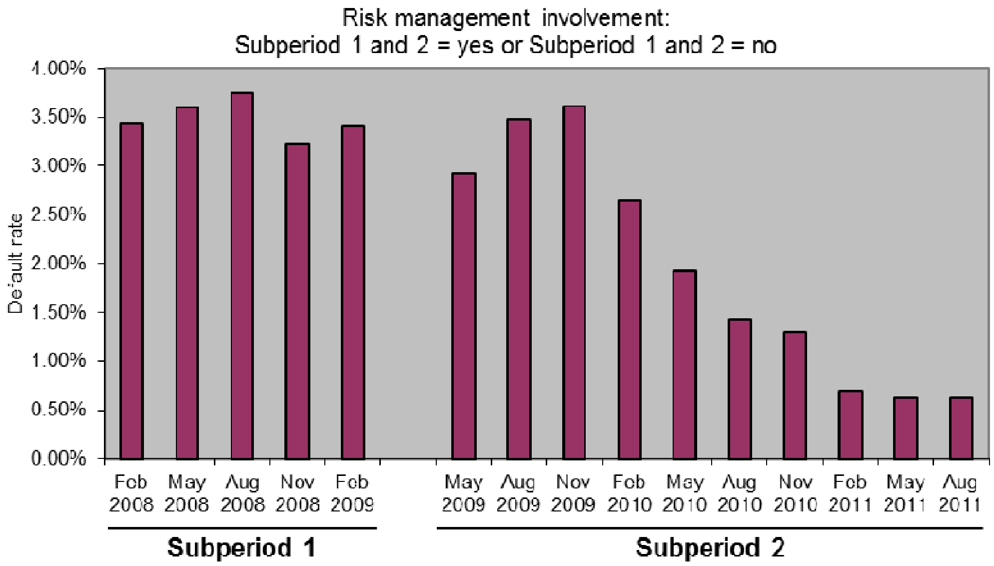
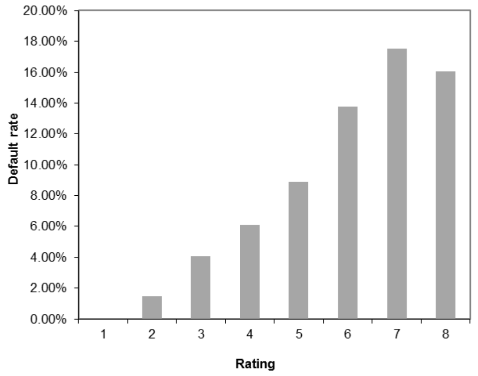


Figure 6: Regression discontinuity – Graphical presentation

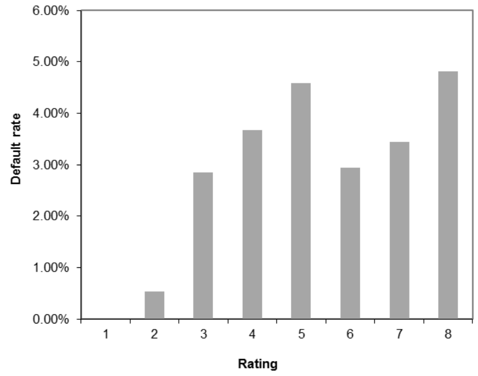
This figure depicts standard regression discontinuity graphs for all loan applications with an LTV between 90% and 100%. The left-hand panel provides graphs for subperiod 1 (February 2008 – April 2009) and the right-hand panel provides graphs for subperiod 2 (May 2009 to September 2011). Panel A provides default rates over the first 24 months after the loan start date by rating grade, with a rating of 5.5 being the threshold for risk management involvement in subperiod 2. Panel B provides mean values of the control variables scaled to a value of 1.0 for a rating of 4.0. Panel C provides a distribution of loan applications by rating grade.

Subperiod 1	**Subperiod 2**

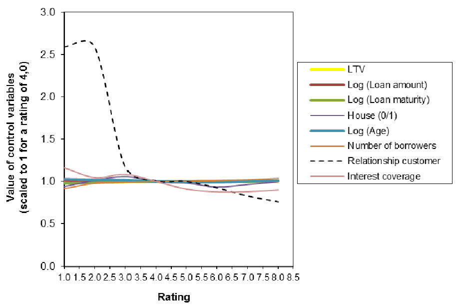
Panel A: Default rates (Subperiod 1)



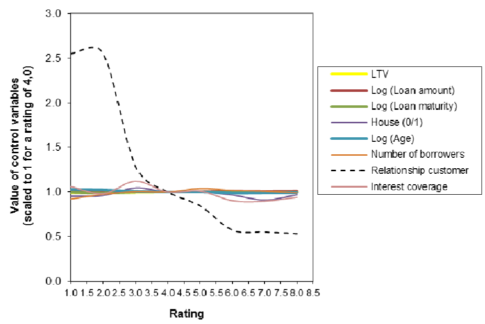
Panel A: Default rates (Subperiod 2)



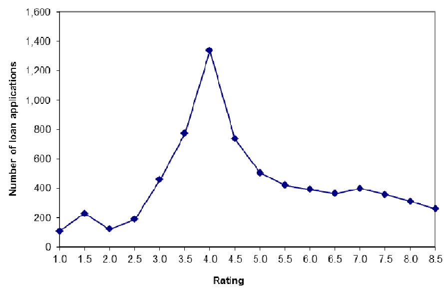
Panel B: Covariates (Subperiod 1)



Panel B: Covariates (Subperiod 2)



Panel C: Distribution of loan applications (Subperiod 1)



Panel C: Distribution of loan applications (Subperiod 2)

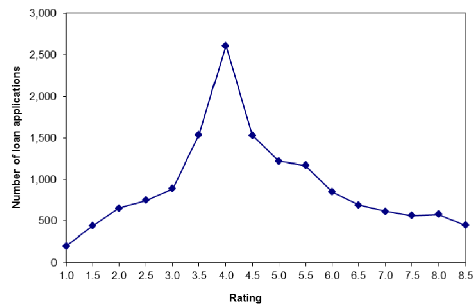


Table 1: Explanation of variables

Name	Description
Key variables	
Risk management involvement (0/1)	Dummy variable equal to one if a loan application has to be approved by risk management
Affected (0/1)	Dummy variable equal to one for all Rating-LTV combinations where no Risk Management Involvement is necessary to approve a loan in Subperiod 1 Risk Management Involvement is necessary in Subperiod 2. These Rating-LTV combinations are: Ratings 6, 7, and 8 for 90% < LTVs ≤ 100%, rating 8 for 72% < LTVs ≤ 90%.
Rating	Internal rating ranging from 1 (best) to 12 (worst).
LTV	Loan-to-Value, determined by dividing the loan amount by the value of the collateral (i.e. the value of the house or apartment)
Loan granted (0/1)	Dummy variable equal to 1 if a loan is granted to the customer. Loans can only be granted to the customer if the loan officer and, if risk management involvement is necessary, a risk manager has approved the loan.
Default (0/1)	Dummy variable equal to 1 if a borrower has defaulted during the first 24 months after the loan start date.
Time and dates	
Subperiod 1	Time period from February 2008 to April 2009
Subperiod 2	Time period from May 2009 to September 2011
After (0/1)	Dummy variable equal to one if the date of the date of the loan application is in Subperiod 2, i.e. during or after May 2009
Date of loan application	Initial day of the loan application. It is the first day where all information is available that is necessary to determine whether risk management needs to be involved or not (in particular: Rating, LTV).
Time	Year fraction between the date of the loan application and May 1st 2009, for example, months is equal to -1/12 for loan applications in April, 1st, 2009 and it is equal to -3/12 for loan applications on July, 1st, 2009.
Loan start date	Date when loan is disbursed. If loan is disbursed in several tranches, the date where the first tranche is disbursed.
Loan characteristics	
Loan amount	Loan amount in EUR
Loan maturity	Loan maturity in months
Bank's expected recovery rate	Bank's expected recovery rate of the bank at the time of origination. The expected recovery rate is based on an internal model taking into account the location and type of the collateral.
House (0/1)	Dummy equal to one if the collateral is a house, and equal to zero if the collateral is an apartment.
Customer characteristics	
Age	Age of customer. If a loan application has several customers, e.g., husband and wife, the average age is used.
Number of borrowers	Number of customers per loan. The number of customers is equal to one is a single person is liable for the loan, it is equal to two if two persons (for example, husband and wife) are liable for the loan.
Relationship customer	Dummy variable equal to 1 if the customer had a checking account or a current loan with the bank before the loan application.
Interest coverage ratio	(Income – Costs) / (Loan Amount + Preexisting liabilities), where income is the yearly net income of the customer in EUR, costs are the non-discretionary costs of living of the customer in EUR, loan amount is the loan amount in EUR and preexisting liabilities are liabilities that exist at the time of loan origination, such as student loans, credit card debt or consumer loans.
Loan officer characteristics	
High experience (0/1)	Dummy equal to one if a loan officer has handled more loan applications over the past 12 months than the median loan officer.

Table 2: Examples

This table provides examples of decisions by risk management.

No.	Applicaion	Decision	Rationale
1	Couple, both 45 years old, apply for a mortgage to buy an old house that needs refurbishment. Two expensive car loans outstanding, no equity.	Reject	• Small amount of equity at this age and car loans outstanding suggest poor savings behaviour in the past. • No consideration of costs needed to refurbish house, likely to require additional financial resources. Implies that purchase of house not a well thought-out plan.
2	Loan applicant owns another one bedroom apparment. Income from this apartment entered twice (rent income and other income), and with the gross amount (includes utilities and heating) instead of the net amount that constitutes income to the owner.	Reject	• Ability to service the mortgage not safe enough after adjusting misspecified rent income.
3	33-year old Indian woman, lives in Europe since 1.5 years and works as an IT specialist, applies for a 15-year EUR 300,000 mortgage loan with payments from the mortgage loan summing up to 60% of net income. EUR 100,000 equity available.	Accept	• Permanent visa not tied to specific employer, IT specialists in high demand in the city she lives in, so job risk seems to be low. • Given her age, significant amount of savings available, account shows regular savings behavior. • Relatively short maturity of loan and young age means that mortgage payments can be reduced by extending the maturity of the loan.
4	Young couple, 30 years old, both working on a fixed-term contract, apply for a EUR 500,000 mortgage. Current income sufficient, but not with a big margin of error, to cover mortgage rates, no equity.	Accept	• CV requested. CV shows that both have studied at top universities abroad with top grades and several internships at renowned firms. This implies that current income is likely to be achieved in the future when fixed-term contract expires.

Table 3: Descriptive statistics

This table presents summary statistics for the sample of all loan applications between February 2008 and September 2011. Column (1) provides summary statistics for loan applications without risk management involvement, column (2) provides summary statistics for loan applications that have to be approved by risk management. For variable definitions see Table 1.

		(1)				(2)			
		Without risk management involvement				With risk management involvement			
		N	Mean	Median	Std.Dev.	N	Mean	Median	Std.Dev.
Key variables									
Rating	Number (1=Best, 8=Worst)	67,860	3.75	4.00	1.69	8,512	5.78	6.00	1.94
LTV		67,860	70.69%	75.41%	24.24%	8,512	102.06%	100.00%	9.35%
Loan granted	Dummy (0/1)	67,860	43.01%	0.00%	49.51%	8,512	28.42%	0.00%	45.11%
Default rate		29,184	2.81%	0.00%	16.52%	2,419	3.18%	0.00%	17.56%
Other loan characteristics									
Loan amount	EUR	67,860	116,039	100,000	78,008	8,512	139,422	122,000	82,865
Loan maturity	Months	67,860	120.00	120.00	43.00	8,512	124.00	120.00	39.00
Bank's expected recovery rate		67,860	77.15%	77.38%	12.36%	8,512	69.32%	70.85%	8.50%
House (0/1)	Dummy (0/1)	67,860	77.13%	100.00%	42.00%	8,512	66.91%	100.00%	47.06%
Other customer characteristics									
Age	Years	67,860	43.50	43.00	10.40	8,512	38.44	38.00	8.95
Number of borrowers	All	67,860	1.67	2.00	0.51	8,512	1.43	1.00	0.53
Relationship customer	Dummy (0/1)	67,860	0.63	1.00	0.48	8,512	0.41	0.00	0.49
Interest coverage		67,860	31.30%	21.79%	62.81%	8,512	20.95%	17.37%	16.75%

Table 4: Default rates by rating and LTV

This table provides default rates over the first 24 months after the loan start date by rating and LTV. Cells shaded in green indicate Rating-LTV combinations without risk management involvement, cells shaded in yellow indicate Rating-LTV combinations where risk management approval is necessary to grant a loan. Panel A presents default rates for Subperiod 1 (February 2008 – April 2009), Panel B presents default rates for Subperiod 2 (May 2009 – September 2011).

Panel A: Subperiod 1 (February 2008 – April 2009)

	LTV					
Rating	< 72%	72%-90%	90%-100%	> 100%	Total	Number of loans
1,2	0.53%	1.83%	0.65%	0.00%	0.83%	1,445
3,4	1.89%	2.59%	5.26%	1.77%	3.25%	5,050
5	3.13%	4.15%	9.36%	5.26%	6.27%	1,149
6	4.67%	4.30%	14.15%	6.25%	9.39%	863
7	5.88%	7.00%	17.44%	7.14%	11.95%	862
8	4.09%	11.35%	15.97%	6.25%	11.54%	641
Total	2.22%	3.75%	8.71%	2.97%	5.05%	10,010
Number of loans	3,558	2,213	3,802	437	10,010	

Panel B: Subperiod 2 (May 2009 – September 2011)

	LTV					
Rating	< 72%	72%-90%	90%-100%	> 100%	Total	Number of loans
1,2	0.17%	0.51%	0.38%	0.00%	0.28%	5,024
3,4	0.73%	1.40%	3.42%	0.58%	1.76%	9,588
5	0.81%	1.72%	4.36%	3.53%	2.48%	3,059
6	1.66%	2.54%	2.54%	4.04%	2.37%	1,860
7	2.17%	6.84%	3.46%	5.08%	4.59%	1,241
8	2.48%	3.77%	4.84%	4.00%	3.65%	821
Total	0.73%	1.97%	3.20%	1.79%	1.81%	21,593
Number of loans	8,919	5,681	6,212	781	21,593	

Table 5: Effect of risk management involvement on default rates – Parallel trend assumption

This table provides results of a test for parallel trends in default rates between rating-LTV combinations affected by the change in risk management threshold and the control group (rating-LTV combinations not affected by the change of the risk management threshold). The dependent variable is a default dummy equal to one if a loan defaults over the first 24 months after the loan start date. The model is estimated using a logistic regression. *Time* is a variable that measures the time between the date of the loan application and May 1st, 2009 and it is measured as a year-fraction (e.g. *Time* is equal to -0.5 for a loan application from Nov. 1st, 2009). *Affected* is a dummy variable equal to one for all rating-LTV combinations where no risk management involvement is necessary to approve a loan in subperiod 1 but risk management involvement is necessary in subperiod 2 (these Rating-LTV combinations are: Ratings 6, 7, and 8 for 90% < LTVs ≤ 100%, rating 8 for 72% < LTVs ≤ 90%). For variable definitions see Table 1. Z-values based on standard errors clustered at the branch level are reported in parentheses. ***, **, * denote significance at the 1, 5 and 10 % level, respectively.

	(1)		(2)		(3)		(4)		(5)	
Dependent	Default (0/1)		Default (0/1)		Default (0/1)		Default (0/1)		Default (0/1)	
Model	Logit		Logit		Logit		Logit		Logit	
Sample	5 quarters before May 2009		4 quarters before May 2009		3 quarters before May 2009		2 quarters before May 2009		1 quarters before May 2009	
Parameter	Odds Ratio	z-stat	Odds Ratio	z-stat	Odds Ratio	z-stat	Odds Ratio	z-stat	Odds Ratio	z-stat
TIME TREND										
Time	0.993	(-0.44)	0.988	(-0.67)	0.974	(-0.72)	0.962	(-0.63)	1.027	(0.17)
Time x Affected	0.996	(-0.16)	1.004	(0.12)	1.047	(0.70)	1.106	(1.10)	1.254	(0.61)
CONSTANTS										
Constant	0.035***	(-21.59)	0.034***	(-20.68)	0.032***	(-17.29)	0.031***	(-15.18)	0.036***	(-16.62)
Affected	4.864***	(10.50)	4.977***	(9.45)	5.665***	(6.78)	6.578***	(7.27)	6.358***	(4.58)
Diagnostics										
Adj. R^2	0.06		0.06		0.05		0.06		0.05	
N	10,010		8,076		5,614		3,600		1,689	

Table 6: Effect of risk management involvement on default rates – Difference in difference approach

This table estimates the effect of risk management involvement on default rates using a difference-in-difference approach. The dependent variable is a default dummy equal to one if a loan defaults over the first 24 months after the loan start date. The model is estimated using a logistic regression. *Affected* is a dummy variable equal to one for all rating-LTV combinations where no risk management involvement is necessary to approve a loan in subperiod 1 but risk management involvement is necessary in subperiod 2 (these Rating-LTV combinations are: Ratings 6, 7, and 8 for 90% < LTVs ≤ 100%, rating 8 for 72% < LTVs ≤ 90%). For variable definitions see Table 1. Z-values based on standard errors clustered at the branch level are reported in parentheses. ***, **, * denote significance at the 1, 5 and 10 % level, respectively.

	(1)		(2)		(3)		(4)		(5)	
Dependent	Default (0/1)		Default (0/1)		Default (0/1)		Default (0/1)		Default (0/1)	
Model	Logit		Logit		Logit		Logit		Logit	
Sample	Total		Total		Total		Total		Total	
Parameter	Odds Ratio	z-stat	Odds Ratio	z-stat	Odds Ratio	z-stat	Odds Ratio	z-stat	Odds Ratio	z-stat
INFERENCE										
Affected x After	0.414***	(-4.54)	0.400***	(-4.66)	0.409***	(-4.57)	0.392***	(-4.75)	0.407***	(-4.57)
Affected	5.010***	(13.96)	1.144	(0.83)	1.134	(0.76)	1.277	(1.46)	1.231	(1.24)
After	0.478***	(-6.91)	0.507***	(-6.16)	0.482***	(-6.32)	0.458***	(-6.65)	0.463***	(-6.69)
RATING (Reference: Rating =1)										
Rating = 2			3.896**	(2.32)	4.138**	(2.42)	4.369**	(2.52)	4.325**	(2.51)
Rating = 3			8.083***	(3.38)	8.884***	(3.53)	7.335***	(3.22)	7.047***	(3.15)
Rating = 4			13.768***	(4.35)	15.088***	(4.50)	12.524***	(4.23)	11.892***	(4.13)
Rating = 5			17.423***	(4.73)	18.952***	(4.86)	15.932***	(4.59)	15.293***	(4.50)
Rating = 6			24.593***	(5.23)	26.041***	(5.33)	19.490***	(4.81)	18.912***	(4.73)
Rating = 7			37.624***	(5.89)	39.388***	(5.95)	28.984***	(5.42)	28.189***	(5.35)
Rating = 8			35.800***	(5.74)	38.209***	(5.84)	28.126***	(5.28)	27.773***	(5.23)
LTV (Reference: LTV>100%)										
LTV ≤ 72%			0.673	(-1.52)	0.902	(-0.43)	1.311	(1.10)	1.340	(1.21)
72% ≤ LTV <= 90%			1.191	(0.79)	1.411*	(1.68)	1.964***	(3.22)	2.078***	(3.63)
90% ≤ LTV <= 100%			2.362***	(3.50)	2.480***	(3.73)	3.021***	(4.68)	3.096***	(4.85)
Other customer controls	No		No		Yes		Yes		Yes	
Other loan controls	No		No		No		Yes		Yes	
Region fixed effects	No		No		No		No		Yes	
Diagnostics										
Adj. R^2	0.06		0.11		0.13		0.16		0.16	
N	31,603		31,603		31,603		31,603		14,748	

Table 7: Difference in difference approach – Establishing that the change in default rates is concentrated around May 2009

This table provides results of various regressions that aim to ensure that the change in default rates for the affected rating-LTV combinations is concentrated around May 2009, i.e. the time where the thresholds for risk management involvement were changed. The dependent variable is a default dummy equal to one if a loan defaults over the first 24 months after the loan start date. The model is estimated using a logistic regression. Column (1) provides results for a narrow time period (+/- 4 quarters) around May 2009, column (2) adds separate time trends for the affected and the non-affected groups. Column (3) allows these time trends to differ pre and post May 2009 and column (4) estimates a flexible 3rd order polynomial for affected and non-affected groups both before and after May 2009. *Affected* is a dummy variable equal to one for all rating-LTV combinations where no risk management involvement is necessary to approve a loan in subperiod 1 but risk management involvement is necessary in subperiod 2 (these Rating-LTV combinations are: Ratings 6, 7, and 8 for 90% < LTVs ≤ 100%, rating 8 for 72% < LTVs ≤ 90%). For variable definitions see Table 1. Z-values based on standard errors clustered at the branch level are reported in parentheses. ***, **, * denote significance at the 1, 5 and 10 % level, respectively.

	(1)		(2)		(3)		(4)	
Dependent	Default (0/1)		Default (0/1)		Default (0/1)		Default (0/1)	
Model	Logit		Logit		Logit		Logit	
Sample	+/- 4 quarters around event		+/- 4 quarters around event		+/- 4 quarters around event		Total	
Parameter	Odds Ratio	z-stat	Odds Ratio	z-stat	Odds Ratio	z-stat	Odds Ratio	z-stat
INFERENCE								
Affected x After	0.371***	(-3.13)	0.361**	(-2.50)	0.203**	(-2.21)	0.299**	(-1.97)
Affected	1.292	(1.28)	1.310	(0.91)	1.265	(0.74)	1.694	(1.18)
After	0.787*	(-1.75)	1.027	(0.11)	1.018	(0.07)	0.747	(-1.24)
TIME TRENDS								
Time trend affected			0.981	(-0.68)				
Time trend non-affected			0.980	(-1.36)				
TIME TRENDS PRE								
Time trend pre affected					0.972	(-1.06)	Yes, 3rd order polynomial	
Time trend pre non-affected					0.976	(-1.22)	Yes, 3rd order polynomial	
TIME TRENDS POST								
Time trend post affected					1.077	(0.84)	Yes, 3rd order polynomial	
Time trend post non-affected					0.984	(-0.83)	Yes, 3rd order polynomial	
Rating controls	Yes		Yes		Yes		Yes	
LTV controls	Yes		Yes		Yes		Yes	
Other customer controls	Yes		No		Yes		Yes	
Other loan controls	Yes		No		Yes		Yes	
Region fixed effects	Yes		No		No		Yes	
Diagnostics								
Adj. R^2	0.16		0.16		0.16		0.18	
N	14,748		14,748		14,748		31,603	

Table 8: Effect of risk management involvement on default rates – Regression discontinuity approach

This table estimates the effect of risk management involvement on default rates using a regression discontinuity approach. The sample is based on all loans during subperiod 2 with an LTV between 90% and 100%. The dependent variable is a default dummy equal to one if a loan defaults over the first 24 months after the loan start date. The model is estimated using a logistic regression (columns (1)-(3)) and a linear regression (columns (4) and (5)). *Risk Management Involvement (0/1)* is a dummy variable equal to one if risk management involvement is necessary to approve a loan (rating 6-8). For variable definitions see Table 1. Z-values (t-value for column (4) and (5)) based on standard errors clustered at the branch level are reported in parentheses. ***, **, * denote significance at the 1, 5 and 10 % level, respectively.

	(1)		(2)		(3)		(4)		(5)	
Dependent	Default (0/1)		Default (0/1)		Default (0/1)		Default (0/1)		Default (0/1)	
Model	Logit		Logit		Logit		Linear		IV	
Sample	Subperiod 2, LTV 90-100%		Subperiod 2, LTV 90-100%		Subperiod 2, LTV 90-100%		Subperiod 2, LTV 90-100%		Subperiod 2, LTV 90-100%	
Methodology	Local regression +/- 2 notches around RMI cutoff		Local regression +/- 2 notches around RMI cutoff		Local regression +/- 2 notches around RMI cutoff		Local regression +/- 2 notches around RMI cutoff		Local regression +/- 2 notches around RMI cutoff	
Parameter	Odds Ratio	z-stat	Odds Ratio	z-stat	Odds Ratio	z-stat	Coeff.	t-stat	Coeff.	t-stat
INFERENCE										
Risk mgmt involvement (0/1)	0.343**	(-2.50)	0.313***	(-2.62)	0.315***	(-2.65)	-0.033***	(-2.90)	-0.029*	(-1.73)
RATING										
(Rating-CutOff) x Affected	1.104	(0.58)	1.168	(0.92)	1.166	(0.94)	0.006	(0.91)	0.007	(1.48)
(Rating-CutOff) x (1-Affected)	1.893**	(2.18)	1.762*	(1.87)	1.743*	(1.83)	0.015	(1.61)	0.005	(0.55)
Other customer controls	No		Yes		Yes		Yes		Yes	
Other loan controls	No		Yes		Yes		Yes		Yes	
Region fixed effects	No		No		Yes		Yes		Yes	
Diagnostics										
Pseudo. R^2 / Adj. R^2	0.01		0.08		0.09		0.03		0.03	
N	4,013		4,013		4,013		4,013		4,013	
FIRST-STAGE REGRESSION										
Initial Rating > RMI cutoff									0.897***	(69.49)
Other customer controls									Yes	
Other loan controls									Yes	
Region fixed effects									Yes	
Adj. R^2									0.86	
N									4,013	

Table 9: Robustness tests - Regression discontinuity

This table provides robustness test for the regression discontinuity approach. The sample is based on all loans during subperiod 2 with an LTV between 90% and 100%. In column (1) to (3), the dependent variable is a default dummy equal to one if a loan defaults over the first 24 months after the loan start date. In column (4), the dependent variable is a loss variable that is constructed by multiplying the default dummy by (1-Expected recovery rate). The models are estimated using a logistic regression (columns (1)-(2)) and a linear regression (columns (3)-(4)). Only coefficients on the main variable of interest, the risk management involvement dummy, are reported. For variable definitions see Table 1. Z-values (t-value for column (3) and (4)) based on standard errors clustered at the branch level are reported in parentheses. ***, **, * denote significance at the 1, 5 and 10 % level, respectively.

	(1)		(2)		(3)		(4)	
Dependent	Default (0/1)		Default (0/1)		Default (0/1)		Loss	
Model	Logit, Odds Ratios		Logit, Marginal Effects		Linear		Linear	
Sample	Subperiod 2, LTV 90-100%		Subperiod 2, LTV 90-100%		Subperiod 2, LTV 90-100%		Subperiod 2, LTV 90-100%	
Parameter	Odds Ratio	z-stat	Average marginal effects	z-stat	Coeff.	t-stat	Coeff.	t-stat
METHODOLOGY								
LOCAL REGRESSION								
Optimal bandwidth (+/- 2 notches around RMI cutoff)	0.315***	(-2.65)	-0.040***	(-2.63)	-0.033***	(-2.90)	-0.010***	(-3.02)
1/2 x Optimal bandwidth (+/- 1 notch around RMI cutoff)	0.227**	(-2.49)	-0.051**	(-2.57)	-0.040***	(-2.91)	-0.015***	(-3.41)
2 x Optimal bandwidth (+/- 4 notches around RMI cutoff)	0.328***	(-3.30)	-0.035***	(-3.26)	-0.033***	(-3.43)	-0.010***	(-3.76)
HIGHER-ORDER POLYNOMIAL								
2nd order	0.246**	(-2.20)	-0.042**	(-2.30)	-0.041***	(-3.19)	-0.013***	(-3.41)
3rd order	0.230**	(-2.24)	-0.044**	(-2.35)	-0.032**	(-2.16)	-0.012***	(-2.78)
4th order	0.218**	(-2.39)	-0.045**	(-2.50)	-0.042**	(-2.39)	-0.016***	(-3.10)

Table 10: Alternative explanations: Experience, Entrenchment

This table provides tests for alternative explanations. Column (1) and (3) provide differential effects of risk management involvement for experienced versus unexperienced loan officers. Experience is measured as the number of loan applications handled over the past 12 months, with the dummy *High Experience* being equal to one if experience exceeds the median of all loan officers. Column (2) and (4) provide differential effects of risk management involvement for relationship customers versus non relationship customers. While column (1) and (2) provide results for a difference-in-difference estimator, column (3) and (4) provide results for a regression discontinuity design. The sample and regression specification is based on column (5) of Table 6 for the difference-in-difference estimator and on column (3) in Table 8 for the regression discontinuity design. For variable definitions see Table 1. Z-values based on standard errors clustered at the branch level are reported in parentheses. ***, **, * denote significance at the 1, 5 and 10 % level, respectively.

	(1)		(2)		(3)		(4)	
Dependent	Default (0/1)		Default (0/1)		Default (0/1)		Default (0/1)	
Model	Logit		Logit		Logit		Logit	
Identification	Difference-in-Difference		Difference-in-Difference		RDD		RDD	
Alternative explanation	Experience		Collusion		Experience		Collusion	
Parameter	Odds Ratio	z-stat	Odds Ratio	z-stat	Odds Ratio	z-stat	Coeff.	t-stat
KEY INFERENCE VARIABLES								
Affected x After	0.395***	(-2.81)	0.323***	(-4.25)				
Affected x After x High Experience	1.046	(0.11)						
Affected x After x Relationship			1.197	(0.27)				
Risk mgmt involvement (0/1)					0.335**	(-2.55)	0.341**	(-2.44)
Risk mgmt involvement x High Experience					1.047	(0.10)		
Risk mgmt involvement x Relationship							1.192	(0.19)
TWO-WAY AND NON-INTERACTED								
Affected x High Experience	0.938	(-0.28)						
After x High Experience	0.952	(-0.26)						
Affected x Relationship			1.477***	(2.62)				
After x Relationship			0.764	(-1.24)				
After	0.475***	(-5.57)	0.536***	(-3.21)				
Affected	1.282	(1.10)	1.357	(1.44)				
High Experience Dummy	0.971	(-0.22)			0.931	(-0.34)		
Relationship Dummy			0.666***	(-3.23)			0.543**	(-2.07)
Linear function on both sides of cut-off	NA		NA		Yes		Yes	
Rating and LTV controls	Yes		Yes		No		No	
Other customer controls	Yes		Yes		Yes		Yes	
Other loan controls	Yes		Yes		Yes		Yes	
Region fixed effects	Yes		No		Yes		Yes	
Diagnostics								
Pseudo. R^2 / Adj. R^2	0.16		0.15		0.09		0.09	
N	31,603		31,603		4,013		4,013	