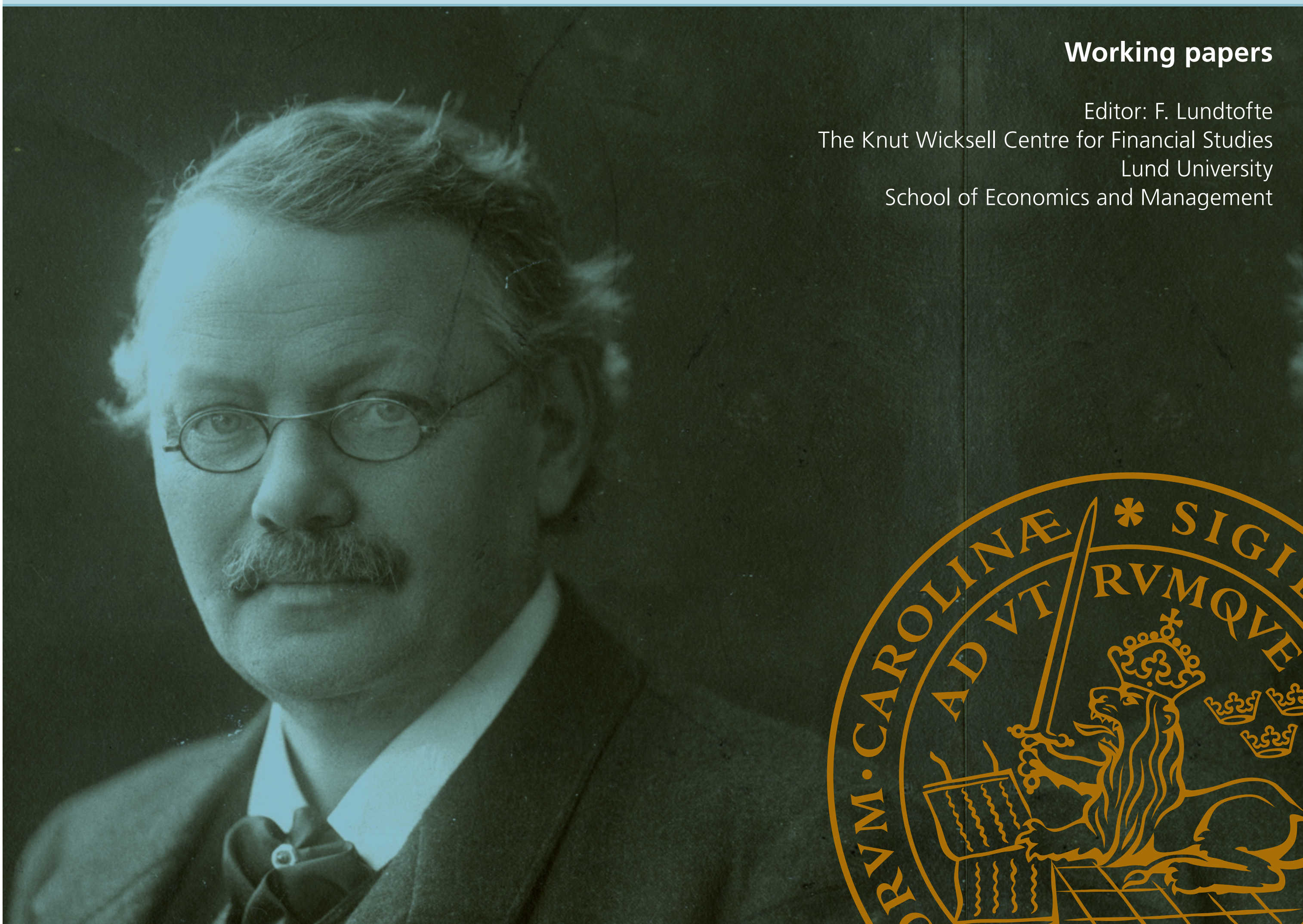
Does Collateral Reduce Loan-Size Credit Rationing? Survey Evidence

ALEMU TULU CHALA & JENS FORSSBÆCK

KNUT WICKSELL WORKING PAPER 2018:6



Working papers

Editor: F. Lundtofte
The Knut Wicksell Centre for Financial Studies
Lund University
School of Economics and Management

Does Collateral Reduce Loan-Size Credit Rationing? Survey Evidence

Alemu Tulu Chala Jens Forssbæck

Abstract

In theory, the use of collateral in credit contracting should mitigate the information problems that are widely held to be the primary cause of credit rationing. However, direct empirical evidence of the link between collateral use and credit rationing is scant. This paper examines the relationship between collateral and credit rationing using survey data that provides clean measures of quantity and loan size rationing. We find that selection problems arising from the loan application process and co-determination of loan terms significantly influence the link between collateral and rationing. Accounting for these problems, our results suggest that collateral reduces the likelihood of experiencing loan-size credit rationing by between 15 and 40 percentage points, and that collateral also decreases the relative loan amount rationed.

1. Introduction

Access to credit is a major concern, particularly for small firms. How important is collateral for securing access to credit for small businesses? The predominant view in the financial intermediation literature is that (equilibrium) rationing in credit markets arises primarily as a consequence of information asymmetries between lender and borrower (Jaffee and Russell, 1976; Stiglitz and Weiss, 1981), and that the provision of collateral by borrowers can work as a signaling or commitment device that addresses the information problems that are the source of credit rationing (Bester, 1985, 1987; Besanko and Thakor, 1987; Chan and Thakor, 1987).[1] Consequently, collateral should reduce credit rationing. Less clear, however, is whether collateral plays an independent role in the presence of alternative mechanisms to overcome informational asymmetries that may substitute for or complement collateral (such as lending relationships, screening/monitoring, or contractual devices other than collateral), and the importance of this role. Despite the strong dependence of small firms on bank credit (Black and Strahan, 2002), their greater information problems, and the wide use of collateral in small business lending (Leeth and Scott, 1989; Cowling, 1999; Berger et al., 2011a), empirical evidence on the link between collateral and

[1] For a review of theoretical contributions on collateral as a device to reduce information asymmetries, see Coco (2000).

rationing remains scarce and essentially only indirect. The empirical literature is also mixed on exactly why collateral is used and by which firms.[2]

The paucity of direct empirical evidence on the relationship between collateral and credit rationing may in large part be due to observability and estimation difficulties. First, the relationship between collateral and credit rationing is virtually impossible to test meaningfully for loan-level data (at least using single-equation specifications). In the case of full "quantity rationing", where a loan applicant is denied credit altogether (also known as borrower rationing), collateral is unobservable simply because no loan transaction ever takes place. In other words, collateral is only observed if there is a loan, which by definition precludes quantity credit rationing. A few recent empirical contributions (Becchetti et al., 2011; Kirschenmann, 2016) have addressed this issue by focusing on "loan size rationing" (Schreft and Villamil, 1992; Kjenstad et al., 2002), where the loan amount granted is lower than the amount applied for (also referred to as loan amount rationing, and directly interpretable as excess demand at the individual borrower level). However, the relative amount granted is only observed if the loan application was not turned down completely. It also requires that the prospective borrower had a credit demand to begin with, and made an application. All these prior outcomes may be influenced by factors that also determine loan amount rationing, suggesting that estimation of this type of rationing necessarily implies working with a non-random sample, with selection bias as the likely consequence.

A second problem related to estimation is that even if one disregards the process whereby a loan came to be approved, loan contracting terms are simultaneously determined (Brick and Palia, 2007). This co-determination may include, for instance, the relative loan amount granted (rationing), the loan interest rate, as well as any collateral requirements. Another way to frame this problem is to note that under the maintained hypothesis that collateral addresses the information problems that are at the root of credit rationing, the extent to which such problems are present jointly determines both collateral use and rationing. The same argument may extend also to observable firm characteristics – whether they are proxies of information availability (such as firm age, size, or the length or scope of the lender-borrower relationship) or other characteristics, such as credit risk, that are believed to influence both collateral and rationing. Thus, even after accounting for non-random selection of the observed sample, endogeneity concerns remain.

The aim of this paper is to test the direct relationship between collateral provision and credit rationing. We use survey data drawn from the 1993, the 1998 and the 2003 versions of the Survey of Small Business Finances (SSBF), conducted by the Federal Reserve Board, which provides us with a total of 11,503 firm-level observations with detailed responses regarding the respondent

[2] For a survey focusing on recent empirical evidence on the determinants of collateral (with implications for credit rationing), see Steijvers and Voordeckers (2009). At a general level, Haselman et al. (2010) find that discrete changes in collateral law are more important than bankruptcy creditor rights for credit supply.

firms' recent credit application experiences.[3] We focus on loan size rationing (whether the borrower was granted the full amount applied for) in the final loan level estimations, so that there is variation in rationing for the approved loans for which we can observe collateral, but the data allow us to model the entire loan application and approval process.

To address the above-mentioned selection and endogeneity issues, our estimation is done in two parts. The first part is a three-step sequential selection process, where we use a trivariate probit model to jointly estimate three conditional sequential equations: first, firms' credit demand; second, firms' propensity to apply for a loan (conditional on credit demand); and third, the likelihood of loan approval (given a firm's credit demand and application decision). The second part estimates the effect of collateral on loan size credit rationing, allowing for endogenously determined collateral and loan interest rates, and accounting for selection bias arising from the loan application process estimated in the first part.

The trivariate probit selection model shows that demand for credit, the firm's decision whether to apply for a loan, and the lender's decision whether to approve the application are a sequence of strongly interrelated outcomes, suggesting that the estimate of the effect of collateral on loan size rationing is likely to be biased if non-random selection is left unaccounted for. In fact, when we ignore selectivity issues and treat collateral and interest rates as exogenous in a set of benchmark regressions, we find little evidence of an effect of collateral on rationing. In contrast, when we control for these potential biases, we find results that are robust both to different proxies of collateral and to alternative estimation methods. The results show that collateral not only reduces the likelihood of experiencing loan size rationing, but also reduces the proportion of the loan amount rationed.

The rest of the paper is structured as follows. The next section gives a brief review of theoretical and empirical literature on credit rationing and collateral, Section III describes the methodology and estimation framework, and Section IV provides a detailed description of the data and variable definitions. We present our results in Section V, and Section VI, finally, concludes.

2. Related Literature

The theoretical literature provides several explanations for credit rationing and how collateral might mitigate it. Early theories rely on exogenous restrictions on interest rates (either *ad hoc* assumptions of price rigidity, or institutional constraints, such as usury laws) to explain the occurrence of quantity rationing in the credit market. The implication is that for certain prospective borrowers, there may be no interest rate that a lender is able or allowed to charge at

[3] Survey data has been rather extensively used in the literature, particularly in studies focusing on the determinants of collateral (but also, to some extent, to study credit constraints). To name a few, see, e.g., Chakraborty and Hu (2006); Brick and Palia (2007); Chakravarty and Yilmazer (2009) for studies using the SSBF, and Harhoff and Körting (1998); Lehmann and Neuberger (2001); Cenni et al. (2015) for studies using non-U.S. surveys. A number of other studies use actual loan application data, e.g., Jiménez et al. (2006); Puri et al. (2011); Jiménez et al. (2012).

which its expected return is positive (Freimer and Gordon, 1965; Jaffee and Modigliani, 1969).

The more contemporary view relies on lenders' inability to perfectly observe borrowers' repayment capability, which prevents them from charging interest rates that are sufficiently differentiated to reflect borrower heterogeneity. In this setting, raising the loan rate adversely affects lenders' credit portfolios via sorting and incentive effects: first, average loan quality is reduced, because at a higher interest rate, high-risk borrowers are more likely to self-select into the applicant pool; second, less profits accrue to the borrower, which may induce lower effort levels and/or risk-shifting behavior (Stiglitz and Weiss, 1981, 1987). Consequently, lenders' expected return does not rise monotonically in the interest rate charged due to adverse selection and moral hazard, which may result in a pooling equilibrium loan rate below the market-clearing level that generates excess demand for credit. Some prospective borrowers may then be rationed despite being observationally indistinguishable from borrowers that are approved for a loan, and despite being willing to pay a higher interest rate.

A sizable theoretical literature suggests that collateral provision may mitigate credit rationing by reducing the *ex ante* and/or *ex post* effects of borrower-lender information asymmetries. Since the provision of collateral entails the risk of losing the pledged assets, borrowers with a lower probability of ending up in default states are more likely to pledge collateral, which suggests that low-risk borrowers use collateral to signal repayment capability to the lender (Bester, 1985; Chan and Kanatas, 1985; Besanko and Thakor, 1987). Thus, collateral reduces adverse selection, and should ultimately mitigate credit rationing. Collateral may also serve as an incentive device to prevent moral hazard by discouraging borrowers from switching to riskier investment projects (Bester, 1987; Chan and Thakor, 1987; Boot et al., 1991), by encouraging borrowers to choose a high effort level (Watson, 1984; Innes, 1990), and by deterring strategic default by enforcing loan repayment (Benjamin, 1978; Hess, 1984; Beutler and Grobéty, 2013). Alternative theories suggest collateral as a substitute (rather than a complement) to screening – the "lazy banks" hypothesis (Manove et al., 2001) – or as an instrument to increase the credit decision efficiency of small relationship lenders in the face of competition from arms' length lenders (Inderst and Müller, 2007).

The results of the empirical literature on credit rationing – particularly in terms of pinning down information asymmetries as a primary driver of rationing – are somewhat mixed. The early empirical literature is limited by having to rely on indirect or inferential measurement of rationing for observability reasons made clear above. Specifically, the implication of credit rationing theory that loan rates are rigid, or sticky with respect to base interest rates, has been used. The testing approach of Berger and Udell (1992) focuses on inferring rationing from rigidities in loan pricing (while recognizing that sticky loan pricing is consistent with, but not sufficient evidence of, rationing). They find that rates on loans issued under commitment are essentially as sticky as those on non-commitment loans, which is inconsistent with interpreting loan rate stickiness as a sign of credit rationing (since commitment loans by definition cannot be rationed). In addition, since commitment loans should be less subject to information problems, loan rate stickiness appears largely unrelated to information asymmetries. The results of Berger and Udell (1992) have later been shown to hold for UK data (Cowling, 2010).

Jappelli (1990) appears to have been the first to use survey data to identify constrained ("rationed") borrowers, but studies constrained *consumers*. Levenson and Willard (2000) use survey data (SSBF) to estimate the probability of loan denial (conditional on applying) for *firms*. They find that rationed firms are more likely to be smaller and younger, and owned by the original founder, but conclude rationing to be a minor phenomenon, as do Berger and Udell (1992). Han et al. (2009) likewise use the SSBF to study "self-rationing" (the probability of not applying for a loan for fear of rejection), and find that riskier borrowers in more concentrated markets are more likely to self-ration. Methodologically closer to our paper is the study by Chakravarty and Yilmazer (2009). They focus primarily on the effect of lender-borrower relationships on the loan rate, but in the process find that firm size and age are negatively associated with self-rationing as well as with loan denial, whereas firm risk is positively associated with rationing outcomes. Drakos and Giannakopoulos (2011), testing loan denial conditional on demand and using survey data from Eastern Europe, find a negative effect of firm size (but no effect of firm age or risk). Cenni et al. (2015), using Italian survey data, find only weak evidence of a relationship effect, but otherwise little that suggests an information-asymmetry effect on rationing.

Two recent studies use actual loan application data to study loan size rationing. Becchetti et al. (2011) and Kirschenmann (2016) both find negative effects of firm size and lender-borrower relationships on loan size rationing. Kirschenmann (2016) further finds that rationing decreases as relationships deepen over time, as well as a mixed impact of collateral on credit rationing. A number of other recent papers also use actual loan application data, but focus on supply-side effects on loan denials. Puri et al. (2011) study the effects of aggregate credit shocks on retail lending and find that banks that are more affected by the shock are more likely to ration credit to their loan customers, but also that rationing occurs across the entire spectrum of borrower risk with very little migration to "quality" borrowers. In a similar vein, Jiménez et al. (2012) find strong positive effects of lender banks' capital and liquidity ratios and profitability on the probability of granting a loan to otherwise comparable borrowers, which appears inconsistent with the notion that rationing occurs primarily (or at least only) as a consequence of borrower characteristics.

A methodologically different approach is the use of disequilibrium models to study credit rationing. Existing studies in this vein reach conflicting results when it comes to the effect of collateral: whereas Ogawa and Suzuki (2000) and Atanasova and Wilson (2004) suggest that collateral increases loan supply, using borrowers' land assets and total assets, respectively, as proxies for collateral, Shen (2002) suggests it does not. Carbo-Valverde et al. (2015) use a disequilibrium approach to study the effect of securitization on credit rationing, and find that lenders' reliance on securitization reduces rationing under normal periods, but some types of securitized assets aggravate borrowers' credit constraints in crisis periods, i.e., they find further evidence of supply-side effects on credit rationing.

The existing evidence on the determinants of collateral is likewise mixed, and evidence of the role of information asymmetries relies, again, on indirect proxies. In addition, evidence that collateral reduces information asymmetries gives only indirect evidence on the role of collateral for credit rationing. A main concern in the literature is the question whether collateral primarily solves adverse selection problems (which is typically taken to imply a negative relationship between firm risk and collateral, since collateral then works as a quality signaling device), or if it is primarily a disciplining mechanism to prevent moral hazard (a positive relationship between firm risk and collateral is assumed). Although theoretically, both adverse selection and moral hazard contribute to credit rationing, whether one or the other is more important may play out on the expected effect of collateral on credit rationing, because if the moral hazard motivation dominates but collateral imperfectly compensates for borrower risk, then loans that are more likely to be collateralized are also more likely to be rationed. For example, Berger and Udell (1992) find (indirect) evidence of somewhat higher rationing for collateralized loans, and interpret the finding in terms of borrower information problems that are not fully resolved by collateral. If, on the other hand, high quality borrowers use collateral as a signal to overcome adverse selection, then collateralized loans should be *less* subject to rationing.[4]

A large number of studies directly test the determinants of collateral. Many of these use survey data (Leeth and Scott, 1989; Avery et al., 1998; Harhoff and Körting, 1998; Cowling, 1999; Hernández-Cánovas and Martínez-Solano, 2006), most test the incidence of collateral as a binary outcome, but a number of studies also test determinants of the *amount* of collateral (Machauer and Weber, 1998; Lehmann and Neuberger, 2001; Menkhoff et al., 2006; Jiménez et al., 2006). With few exceptions – Brick and Palia (2007) is one – empirical studies on the determinants of collateral do not account for the simultaneous determination of different price and non-price loan contract features (such as loan interest rate and collateral), suggesting results should be interpreted primarily as correlations. A limited number of more recent studies (partially) account for incidental truncation (Chakraborty and Hu, 2006).

Although evidence overall is mixed, when it comes to basic firm characteristics, one result appears universally consistent: firm age is negatively associated with collateral use. The conventional argument is that, unlike startups and young businesses, older firms have track records, tractable credit histories, etc. (Berger and Udell, 1995) – in short, are less subject to information problems. Similar consistency does not appear for other basic firm characteristics, such as firm size, which alternately take on positive (Berger and Udell,

[4] It can be noted that lower *observable* risk of borrowers that were granted a loan is not necessarily a good proxy of unobserved borrower quality, particularly if high-quality borrowers opt out of the applicant pool due to adverse selection and/or low-quality borrowers are denied loans altogether; in turn, higher risk does not necessarily proxy for moral hazard: a borrower can have high *ex ante* observed credit risk, but have a high-quality project and not be prone to shirking or risk-shifting.

1995; Chakraborty and Hu, 2006) and negative (Degryse and Cayseele, 2000; Lehmann and Neuberger, 2001) associations with collateral, or firm credit risk, which is equally sometimes estimated to have a positive (Machauer and Weber, 1998; Jiménez et al., 2006) and sometimes a negative (Lehmann and Neuberger, 2001) relationship with collateral. Several studies also find significant effects of firm type (legal or incorporation status) and/or industry. Evidence on the latter may be interpreted as somewhat consistent with the notion that firms in industries with a high share of tangible assets (such as real estate, manufacturing, or retail trade) are more likely to have collateralized loans (Leeth and Scott, 1989; Berger and Udell, 1995; Avery et al., 1998; Harhoff and Körting, 1998). Results on the relationship between collateral and other loan terms are, again, mixed. Whereas collateral appears to be relatively consistently more likely for larger loan amounts (Leeth and Scott, 1989; Degryse and Cayseele, 2000; Jiménez et al., 2006; Berger et al., 2011a), it is associated with higher loan rates in some studies (Berger and Udell, 1990, 1992; Brick and Palia, 2007) and with lower rates in others (Machauer and Weber, 1998; Degryse and Cayseele, 2000; Chakravarty and Yilmazer, 2009). The relationship with maturity is similarly indeterminate (Leeth and Scott, 1989; Harhoff and Körting, 1998; Degryse and Cayseele, 2000).

A major concern in the literature is also the effect of lender-borrower relationships (Petersen and Rajan, 1994) on collateral use. Relationships and collateral are considered primarily as substitutes, i.e., alternative mechanisms to overcome pre-contractual information asymmetries. Importantly, however (and unlike other loan terms) the duration and scope of prior lender-borrower relationships are unlikely to be endogenous with respect to collateral, since they are – by definition – pre-existing when the loan is contracted. The effect of relationships on collateral appears ambiguous. On the one hand, borrowing from a main bank, or house bank, increases the incidence of collateral, and long-term exclusive relationships with a single bank can also increase collateral or personal commitment requirements (Lehmann and Neuberger, 2001; Menkhoff et al., 2006; Voordeckers and Steijvers, 2006). This could be the result of the "holdup problem" – banks extract rents from firms that are captive with a single lender. On the other hand, there is consistent evidence that the length of prior relationship between lender and borrower decreases the incidence of collateral, which would tend to point in favor of a conventional information-asymmetry story (Berger and Udell, 1995; Chakraborty and Hu, 2006; Jiménez et al., 2006; Brick and Palia, 2007). Another commonly used indicator is the number of bank relationships maintained by the borrower firm, which is found to be positively associated with collateral use in some studies (Harhoff and Körting, 1998; Chakraborty and Hu, 2006), whereas others find the association to be negative or inconclusive (Menkhoff et al., 2006; Jiménez et al., 2006). The effect of relationships could therefore also depend on competition between lenders. The direct effect of competition (typically measured by bank market concentration) on collateral use is, again, inconclusive – for instance, the results of Jiménez et al. (2006) and Voordeckers and Steijvers (2006) point in different directions.

A smaller number of studies use more direct identification strategies to isolate the effect of *ex ante* information availability on credit rationing or on collateral use. Cheng and Degryse (2010) study the effect of information sharing via a public credit registry on the approval of consumer credit card applications by a Chinese bank. They find that information sharing does not affect credit rationing on average, but that sharing of positive information by other banks results in customers receiving higher credit card lines. Berger et al. (2011a) exploit a shift in lenders' access to information about borrowers provided by the adoption of a new credit scoring technology in loan underwriting to investigate whether this reduction in *ex ante* information asymmetry reduces the incidence of collateral, and find that this is the case. Finally, exploiting a legal change that reduced the value of company mortgages (a widely used form of collateral for businesses) in Sweden, and comprehensive data from a single bank, Cerqueiro et al. (2016) find that the bank in response to this exogenous shock to collateral values significantly reduced its internal credit limits to borrowers with collateralized business loans.[5]

To sum up, although the information-asymmetry paradigm dominates the theoretical literature on credit rationing and collateral, the empirical literature does not provide conclusive evidence in support of this view (at the very least, it suggests some additional mechanisms). There is evidence of a role for information asymmetries in both credit rationing and collateral provision, but there are also several open issues and some results that appear to challenge the predominant view. In particular, there is substantial evidence of supply-side effects on rationing, and the effect of observable borrower risk (and possibly other firm characteristics) for collateral use remains unclear, particularly in the presence of competing mechanisms for reducing borrowers' *ex ante* information advantage. There appears to be industry effects, and collateral may mostly be used in industries where information asymmetries are low and tangible assets are high. If collateral works as insurance (rather than as a signaling device), then borrower characteristics may be more important for non-collateralized loans. In that sense, collateral may compensate for (bad) borrower characteristics, and we may not expect a negative effect of collateral incidence on rationing. It may also be the case that for collateralized loans, the value of the collateral is more important than borrower characteristics, possibly suggesting that if credit rationing is influenced by supply-side factors and overall economic conditions or shocks that negatively affect collateral values, then collateralized loans may be more exposed to rationing than non-collateralized loans. For instance, the results of Puri et al. (2011) indicate that mortgage loans are more rationed than (presumably less frequently collateralized) consumer loans as the result of a shock.

3. Methodology

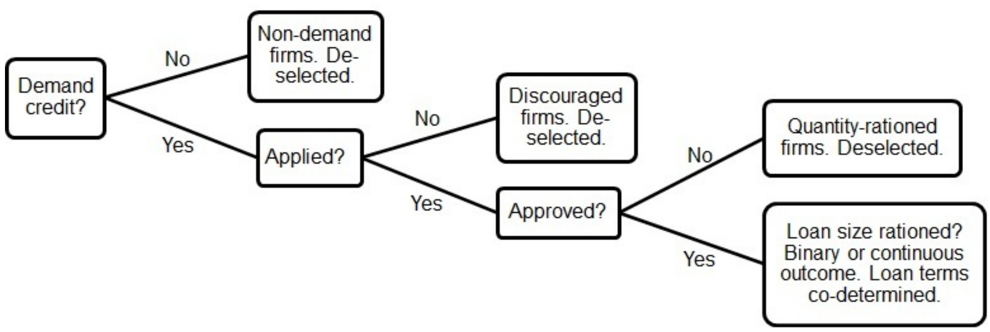
Estimation of the direct relationship between collateral and credit rationing introduces a number of econometric challenges. Our end goal is to estimate

[5] Note that this effect is conditional on there already being a collateralized loan in place.

the determinants of credit rationing. We define firms as credit rationed if we observe that they have unsatisfied demand for credit. Specifically, we focus on loan size rationing (the loan amount granted is lower than the amount applied for) – first, because this provides a clean and intuitive measure of excess demand at the individual borrower level; second, because this is the only possible definition that allows us with certainty to observe other loan terms (including collateral). But firms can only be loan-size-rationed if they are not denied credit altogether, and it is likely that the probability of being loan-size-rationed is determined largely by the same factors that determine loan approval/denial.

Moreover, there may be factors influencing a firm's chances of being approved for a loan that are also related to the likelihood that the firm had a credit demand to begin with, and made a loan application. In particular, loan approval and firms' expectation of loan approval (and therefore their propensity to apply) may depend on the *availability* of collateral. Thus, the sub-sample of firms for which we can observe the extent of loan size rationing is not a random draw from the full sample, which renders estimation of any single-equation model of loan size rationing inappropriate. The non-randomness of the process by which size-rationed loans and loan terms come to be observed is likely to result in biased estimates. In addition, economic reasoning and prior evidence suggest that for loans that are approved, the loan contract terms – including the loan amount as a proportion of the amount applied for – are simultaneously determined, because they are the joint outcome of a bargaining process, and the "package" of loan terms may be driven by common observable and/or unobservable borrower characteristics. To address these issues, we adopt a sequential estimation approach consisting of two main parts. The basic sequence is summarized in Figure 1.[6]

Figure 1
Sequential estimation procedure



[6] The sequence is essentially determined by the design of the SSBF surveys, and similar to the sequential structure in, e.g., Cole and Sokolyk (2016).

The first part is a three-step selection process, modeling how firms end up with an approved loan with observable loan terms. From the total (randomly assigned) sample at our disposal, we first observe whether a firm made a loan application or not. Firms that made a loan application have a manifest loan demand. But there are also firms that do not apply for credit even though they need it. This group of firms are called "discouraged" borrowers (Jappelli, 1990; Kon and Storey, 2003; Han et al., 2009). The survey data allows us to identify this group of firms, which are included among the firms with non-zero credit demand. In latent-variable notation, the first step in the selection process is then:

$$Demand_i^* = \alpha_1 + \beta_{F1}' X_{F,i} + \beta_{G1}' X_{G,i} + \gamma_1' Z_{1,i} + \epsilon_{1,i} \tag{1}$$

where the observable counterpart of $Demand_i^*$ is the indicator variable $Demand_i$, which takes on unit value if firm i either applied for a loan or is identified as a discouraged borrower, X_F is a vector of core firm characteristics, X_G is a set of general control variables (which includes dummies for geographical region and survey release), and Z_1 is a set of indicators constructed from responses to survey questions specifically reflecting the firm's financing situation (detailed variable descriptions are deferred to Section IV).

Equation 1 is estimated for the full sample of firms. The next step in the selection process estimates the probability that a firm applies for a loan (conditional on demand):

$$Applied_i^* = \alpha_2 + \beta_{F2}' X_{F,i} + \beta_{O2}' X_{O,i} + \beta_{G2}' X_{G,i} + \gamma_2' Z_{2,i} + \epsilon_{2,i} \tag{2}$$

where the propensity to apply is proxied by the indicator $Applied_i$, which is equal to one if firm i applied for a loan and zero if i was discouraged from applying. $Applied_i$ is only observed if $Demand_i = 1$, and missing otherwise. X_O is a vector of firm owner characteristics believed to influence discouragement (including, e.g., demographic information and credit history), Z_2 is a set of variables related to alternative sources of credit. The final step in the selection process determines if, conditional on loan demand and application, a firm will be granted *some* loan amount (and therefore will be observed in the sub-sample for which loan terms are available):

$$\begin{aligned} Approved_i^* = \alpha_3 &+ \beta_{F3}' X_{F,i} + \beta_{O3}' X_{O,i} + \beta_{H3}' X_{H,i} + \beta_{G3}' X_{G,i} \\ &+ \gamma_3' Z_{3,i} + \epsilon_{3,i} \end{aligned} \tag{3}$$

where the latent approval rate is represented by the indicator $Approved_i$, which is equal to one if i was approved for a loan, equals zero if i was rejected completely, and is observed only if $Applied_i = 1$. Because all firms that are included in this last step made a loan application, we can observe some loan characteristics (but not all loan terms, since some applications were rejected), and these make up the vector X_H. Z_3 is a set of additional variables influencing loan approval probability.

The selection process is estimated as a trivariate probit with sample truncation, assuming correlated and jointly normally distributed errors, using a full-information maximum likelihood conditional mixed process procedure, where the trivariate cumulative normal distribution is simulated using the Geweke-Hajivassiliou-Keane (GHK) algorithm, see Roodman (2011) for details). Accounting for the selection procedure as described above ensures that the relationship between loan size rationing and loan contract terms that we analyze in the second part of the estimation procedure reflects lenders' decision to restrict the availability of credit and is not biased by non-random sampling effects related to borrowers' demand or likelihood to apply and be approved for credit. We follow the conventional Heckman two-step approach to account for selectivity and calculate the inverse Mills ratios from the selection equations, which are then included as regressors in the second part of the estimation.

This second part is based on an implicit three-equation simultaneous-equations system, where the endogenous variables are a measure of loan size rationing, a variable indicating collateral, and the loan interest rate. We do not specify the full structure of the system, but focus on the main equation of interest:

$$\begin{aligned} \mathit{Credit\ rationing}_i = \alpha_4 + \beta'_{F4} X_{F,i} + \beta'_{O4} X_{O,i} + \beta'_{L4} X_{L,i} + \beta'_{G4} X_{G,i} \\ + \theta_C \widehat{Coll}_i + \theta_S \widehat{Intr}_i + \Pi'_4 M_i + \epsilon_{4,i} \end{aligned} \tag{4}$$

with predictions of collateral and loan rates estimated from reduced-form equations and defined as:

$$\widehat{Coll}_i = \hat{\alpha}_5 + \hat{\beta}'_{F5} X_{F,i} + \hat{\beta}'_{O5} X_{O,i} + \hat{\beta}'_{L5} X_{L,i} + \hat{\beta}'_{G5} X_{G,i} + \hat{\Pi}'_5 M_i + \hat{\gamma}'_5 Z_{CS,i} \tag{5}$$

and

$$\widehat{Intr}_i = \hat{\alpha}_6 + \hat{\beta}'_{F6} X_{F,i} + \hat{\beta}'_{O6} X_{O,i} + \hat{\beta}'_{L6} X_{L,i} + \hat{\beta}'_{G6} X_{G,i} + \hat{\Pi}'_6 M_i + \hat{\gamma}_6 Z_{CS,i} \tag{6}$$

where *Credit rationing* is loan size rationing (measured as an indicator or a continuous variable), $Coll$ is collateral, $Intr$ is the loan interest rate, X_L is the full set of observed loan characteristics (which subsumes X_H from equation 3), M is the vector of inverse Mills ratios from equations 1, 2 and 3, and Z_{CS} are instruments for the loan terms.

This second part of the estimation is initially carried out using linear probability models estimated by IV-GMM although both loan size rationing and collateral are in some estimations observed as binary variables – primarily to facilitate identification testing and to ensure that identification is not based on functional form. In the final regressions, however, we estimate equation 4 using IV-probit or IV-tobit, depending on the definition of the dependent variable.

A potential critique is that we split up rationing into one discrete approval/denial decision, and one decision determining the relative loan amount granted, when these outcomes might, perhaps, be more appropriately seen as different points on a single scale. The relative loan amount granted is a clean measure of rationing because it captures the difference between credit demanded and credit supplied for each prospective borrower. But ideally, this should really also include completely denied borrowers, because for these borrowers the relative amount granted is simply equal to zero. However, for completely denied borrowers, loan contract terms are not observable, so estimating rationing as a single potential outcome in the closed interval [0,1] would necessarily imply having to drop other loan terms as potential explanatory variables. We do the second-best thing, and control for the selection bias inherent in testing only loans that were (partially or fully) granted.

4. Data

4.1 The Survey of Small Business Finances

The data employed in this paper are the 1993, the 1998 and the 2003 releases of the Survey of Small Business Finances (SSBF)[7] – the three most recent in four rounds of surveys conducted by the Federal Reserve at approximately five-year intervals between 1987 and 2003. The surveys cover nationally representative samples of small businesses operating in the U.S. at the end of each survey year, with survey responses collected over approximately three-year periods prior to each release year. Small businesses are defined as firms with less than 500 employees, and the firms covered in the surveys are non-farm enterprises. The surveys provide information about basic characteristics of the firms, including firm age, organizational form, standard industrial classification, and a considerable amount of information on the firms' owner(s). Selected financial-statement data and information on credit history are also covered by the survey.

In addition to firm and owner characteristics, the SSBF also provides information on the most recent borrowing experiences of each firm. The survey data cover information on whether the firm applied for credit, and whether the application was approved or rejected. If the lender extended credit, the survey provides information on the terms of the loan, including interest rate, loan amount and collateral. Importantly, it also covers information on loan applications that were rejected, including type of loan and main reasons that the loan application was rejected, which is the main advantage of the survey data that allows us to control for the sample truncation inherent in studying only loans that are approved. In addition, the surveys provide some (though only very rudimentary) information about the lenders to which the firms applied for loans, and relatively detailed documentation about prior relationships between lender and borrower.

Our analysis pools the observations from the three SSBF releases into one dataset. The total number of firms covered in the surveys is 4,637 (1993), 3,561 (1998) and 4,240 (2003). Besides making the dataset larger, an additional reason for pooling observations across the surveys is that it makes results less sensitive to possible time-specificity and business cycle effects. The three

[7] The SSBF datasets are publicly available and can be downloaded at the Federal Reserve's website `http://www.federalreserve.gov/pubs/oss/oss3/nssbftoc.htm`.

rounds of SSBF, however, differ somewhat from each other with respect to some questions aimed at collecting information on characteristics of firms and their owners. This has implications for the variables we use in that only those variables that the three surveys have in common are included in the analysis.

We apply the following data filtering procedures. First, we limit the sample to non-financial firms by dropping firms from the financial industry (1-digit SIC code equal to 6), following previous empirical literature. Some firms report negative values for total sales; we exclude these observations from the sample. We also exclude firms with approved loan applications that report zero values for loan maturity or loan interest rate. After these restrictions, our final sample contains 11,503 observations.

4.2 Loan Demand, Loan Applications, and Credit Rationing

The section of the 1993 and the 2003 surveys that covers the firms' most recent borrowing experiences includes both new applications for lines of credit and other types of loans and *renewals* of existing lines of credit, whereas the 1998 survey only covers information on applications for new loans. Because we pool the three surveys into one dataset, our analysis focuses on new loan applications only. Applications for credit cards, trade credit with suppliers, or applications that were withdrawn or still pending when the surveys were conducted are not included.

Excluding renewals of existing lines of credit, the firms were asked "How many times in the last three years did the firm apply for new loans?". Based on the response to this question, we construct the binary variable $Applied_i$ to identify firms (i = 1, ..., N) that applied for one or more new loans:

$$Applied_i = \begin{cases} 1 & \text{if single} \vee \text{multiple new loans} \\ 0 & \text{otherwise.} \end{cases} \tag{7}$$

$Applied_i = 0$ includes discouraged borrowers, but these firms need to be distinguished from other non-applicants because they have a credit demand. The dataset allows us to make this distinction. If a firm's response to the question "During the last three years, were there times when [FIRM] needed credit, but did not apply because it thought the application would be turned down?" is YES, we identify the firm as a discouraged borrower:[8]

$$Discouraged_i = \begin{cases} 1 & \text{if } Applied_i = 0 \wedge \text{fear rejection} \\ 0 & \text{otherwise.} \end{cases} \tag{8}$$

[8] Like Chakravarty and Yilmazer (2009), we only define firms as discouraged that *never* applied, but firms that answered YES to this question but still applied at least once are treated as though they were not discouraged. In contrast to Chakravarty and Yilmazer (2009), we account for how firms that did not apply but were not discouraged are deselected from the sample; i.e., we do not simply drop non-demand firms from the sample due to the potential selection bias discussed above.

Based on the responses to the questions on loan applications and fear of rejection, we are able to distinguish between firms with and those without a credit demand. Thus, we define the binary variable $Demand_i$ as:

$$Demand_i = \begin{cases} 1 & \text{if } Applied_i = 1 \lor Discouraged_i = 1 \\ 0 & \text{otherwise.} \end{cases} \quad (9)$$

$Demand_i$ is observed for the full sample of firms, and is the dependent variable in the first step of the selection process (equation 1). $Applied_i$ is the dependent variable in equation 2, and is observed if $Demand_i = 1$ and missing otherwise.

Firms with nonzero loan applications in the last three years were also asked, regarding their most recent loan application, "Was this recent loan application approved or denied?". Based on the response to this question, we define the last dependent variable in the selection process as:

$$Approved_i = \begin{cases} 1 & \text{if approved} \\ 0 & \text{otherwise.} \end{cases} \quad (10)$$

$Approved_i$ is observed if $Applied_i = 1$, and missing otherwise. Firms are defined as quantity-rationed if they made at least one loan application during the previous three years but were not approved for a loan. Among *approved* loan applications, the loan amount granted may be some fraction of the amount applied for. We identify these loans based on responses to the questions "What was the total dollar amount for which the firm applied?" and "What was the dollar amount of the credit granted?". The first question refers to loan demand, the second refers to loan supply. Firms are defined as loan-size-rationed if the supplied loan amount ($Loan_i^s$) for the most recently approved loan is smaller than the demanded amount ($Loan_i^d$). In the analysis, we use the continuous variable $Proportion\ rationed_i$ (i.e., proportion denied), defined as $1 - Loan_i^s / Loan_i^d$, as well as a binary variable indicating loan size rationing, and defined as:

$$Loan\ size\ rationing_i = \begin{cases} 1 & \text{if } Approved_i = 1 \\ & \land\ Loan_i^s < Loan_i^d \\ 0 & \text{otherwise.} \end{cases} \quad (11)$$

4.3 Collateral and Guarantees

Collateral use for approved loans is defined from the firms' response to the survey questions "Was any type of collateral required to secure this most recent loan?" and "Was the firm required to have a personal Guarantee, Cosigner, or other guarantor?". A positive (yes) response to either of these questions gives unit value to the binary variable *Collateral*, which is consequently equal to zero for unsecured loans.

For collateralized loans, firms are asked the follow-up question "What collateral was used to secure this most recent loan?". Possible responses to this question fall within one or several of a total of seven categories of collateral.[9] Based on the answer to this question and on whether or not the loan was secured by a guarantee, we define the alternative measure *#collateral types*, which takes on integer values between 0 and 8, reflecting the number of different types of collateral (including any possible guarantee) that were used to secure a loan.

4.4 Control Variables

We control for several variables that may be systematically related to credit rationing, self-rationing and the determinants of collateral, and our choice of variables included at various stages in the loan application/approval decisions is based both on theoretical considerations and on previous empirical literature (discussed in Section 2). We are also constrained to using data extracted from the survey only: the surveyed firms are anonymized and cannot be matched to alternative data sources (the same holds true for the lenders).[10]

Firm Characteristics: Firm size is measured as (the natural logarithms of) both total sales and the total number of employees, since both revenues and the size of the employee force have proved to be significantly associated with credit demand (Drakos and Giannakopoulos, 2011), self-rationing (Chakravarty and Yilmazer, 2009; Han et al., 2009), loan approval (Chakraborty and Hu, 2006; Chakravarty and Yilmazer, 2009; Drakos and Giannakopoulos, 2011; Carbo-Valverde et al., 2015), collateral (Berger and Udell, 1995; Chakraborty and Hu, 2006), and the proportion of loan amount granted (Kirschenmann, 2016), and they are only modestly correlated. We prefer to use total sales rather than total assets, primarily due to the better distributional properties of the sales figures reported in the data. For instance, there is a substantial number of firms for which total assets take on very large negative values. For the same reason, we scale other firm-level financial variables by total sales.

Another firm characteristic that has been shown relevant for loan application (Chakravarty and Yilmazer, 2009), approval (Chakraborty and Hu, 2006; Chakravarty and Yilmazer, 2009; Jiménez et al., 2012; Carbo-Valverde et al., 2015) and the proportion granted (Kirschenmann, 2016) is firm age. Higher age may proxy better information availability (Diamond, 1989) and high reputational capital (Diamond, 1991). We measure firm age as the logarithm of the number of years the current owner has owned the business. Profitable firms are in a better position to use internally generated funds; hence they may need less external funding (Drakos and Giannakopoulos, 2011). Profitability has also proved to be significantly associated with loan approval (Drakos and Giannakopoulos, 2011; Jiménez et al., 2012). We use earnings scaled by total sales to control for firm profitability. We further include the ratio of total debt to equity to account for firm leverage, which has been related to credit need

[9] The categories are: (1) inventory or accounts receivable, (2) business equipment or vehicles, (3) business securities or deposits, (4) business real estate, (5) personal real estate, (6) other personal assets, and (7) other collateral.

[10] Control variables are included according to the point in the application process from which they become available. E.g., data on the lender from which they firm applied for a loan are only available for firms that made a loan application, and are included from equation 3 onward, etc.

(Cenni et al., 2015), loan rate (Chakravarty and Yilmazer, 2009) and collateral (Berger and Udell, 1995). Both profitability and leverage are winsorized at the first and 99th percentiles to reduce the occurrence of outliers.

In the empirical literature, small business credit scores are commonly used to measure a firm's creditworthiness (Mester, 1997). However, credit scores are not available in the 1993 SSBF dataset, and we instead use the data on firms' credit histories reported in the surveys (Chakraborty and Hu, 2006; Brick and Palia, 2007; Jiménez et al., 2006; Chakravarty and Yilmazer, 2009; Cole and Mehran, 2011). In particular, we construct a dummy variable that takes the value one if in the past seven years the firm has declared bankruptcy, or if the firm in the past three years has had any business obligations past due for 60 days or more, and zero otherwise. The dummy variable *Low diversification* proxies the geographical scope of the business, and takes on unit value if the firm primarily does business in the area where its headquarters are located, and zero otherwise. Finally, variables related to firm characteristics also include dummies for legal incorporation type (C-corporation, S-corporation, partnership, or proprietorship) and industry (1-digit SIC codes).

Owner Characteristics: For small businesses, firm owner characteristics may influence both the propensity to apply for a loan and the likelihood of being approved. One such characteristic is owner education, which naturally lends itself to an interpretation in terms of human capital. We measure education as the dummy variable *College*, which takes on unit value if the data reports the main owner's education level as "college degree" or "post graduate degree", and zero otherwise.[11] We also include the length of the owner's business experience, defined as (the logarithm of one plus) the number of years the owner has worked managing or owning the business. We also include the logarithm of owner age. For firms with multiple owners, age and experience are the weighted averages of the owners.

Though results are somewhat mixed, a number of studies have found that belonging to a minority group can be detrimental to credit access (Gabriel and Rosenthal, 1991; Munnell et al., 1996; Coleman, 2002; Cavalluzzo et al., 2002; Blanchflower et al., 2003; Cavalluzzo and Wolken, 2005). To account for possible discrimination, we include the dummy variable *AfrAm ownership*, which is set to unity if more than 50 percent of the firm is African American owned, and zero otherwise. Similar dummy variables are also included for Asian and Hispanic owners. We also include the dummy variable *Female ownership*, to account for a possible gender effect (Carter et al., 2007). In addition, for small business financing, some studies suggest that there exists little separation between the firm's and the owner's credit risk (Ang et al., 1995). We therefore include a dummy variable that takes the value one if the business owner has declared bankruptcy in the past seven years, or if the owner has any obligation past due for 60 days or more in the past three years, and zero otherwise. Finally, we control for ownership concentration, measured as the percentage ownership share of the primary owner.

[11]The SSBF codes the level of owner education on a seven-step scale: "less than a high school degree", "high school graduate", "some college but no degree granted", "associate degree", "trade school/vocational program", "college degree", and "post graduate degree".

Relationship Characteristics: We include several measures of firm-lender relationships. The first is *Relationship length*, which is calculated as (the log of one plus) the number of years the borrowing firm has conducted business with the lender, and accounts for the strength (duration) of the lending relationship. We also include the *Number of sources* of financial services used by the firm. Lenders may offer multiple financial services as a way to "capture" the firm and build relationships (Boot, 2000). Evidence also suggests that non-credit financial services such as checking and saving accounts help the lender to better monitor different aspects of the firm's business (Mester et al., 2001). An additional relationship measure included is *Distance*, which equals one plus the log of the geographic distance in miles between the firm's and the lender's headquarters, as geographical proximity facilitates the collection and processing of soft information (Berger et al., 2005). We also make use of survey responses to the question "What factors influenced the firm's decision to apply for credit from [institution that approved]?" by including the dummy variable *Referral*, which takes on the value 1 if the reason is "Seller referral" and/or "Other referral", and 0 otherwise. Finally, we set the dummy variable *Previous loan* to unity if the response to the above equation is "Previous loan", and 0 otherwise.

Lender Characteristics: For firms that made at least one loan application, we observe the type of financial institution to which the loan application was made. We control for this by including the dummy variable *Lender type*, which maps the SSBF's lender categories. We collapse the originally reported 21 categories into four overall groups: banks, non-bank financial firms, individuals (owner, family or other), and other lender type. Previous studies have shown that applying for a loan at a "main bank" may improve the likelihood of approval (Lehmann and Neuberger, 2001) as well as influence loan terms (Degryse and Cayseele, 2000; Menkhoff et al., 2006). Thus, we include the variable *Primary bank* which equals 1 if if the financial institution to which the loan application was made is the firm's primary provider of financial services, and 0 otherwise.

Loan Characteristics: For firms with at least one loan application, we observe the type of loan that was most recently applied for, which we control for using the dummy variable *Loan type*, that maps the SSBF's six categories.[12] For approved loans, we also control for the maturity of the loan, measured as the logarithm of the maturity in months. The loan amount applied for has been shown to be significantly associated with collateral (Leeth and Scott, 1989; Degryse and Cayseele, 2000; Jiménez et al., 2006; Berger et al., 2011b). To account for this, we include the amount applied for scaled by the firm's total sales. Besides collateral, the other main loan term that we treat as endogenous is the interest rate of the loan.

Environmental Factors: To control for geographic information, two variables are included. The first one controls for whether the headquarters of the firm are located in an urban (as opposed to a rural) area. The dummy variable *Metropolitan area* takes the value 1 if the firm's headquarters are located in a

[12]The loan types include new credit line, capital lease, mortgage, vehicle loan, equipment loan and other loan.

Metropolitan Statistical Area (MSA), and 0 otherwise. The second is a dummy variable for each of the nine U.S. Census Division regions[13], which is the most detailed location information available for the survey firms. To account for regional bank market structure, we include the dummy variable *Banking concentration*, which equals 1 if the Herfindahl-Hirschman Index (HHI) reported in the surveys is greater than or equal to 1800, and zero otherwise. Finally, dummies for survey release are included to control for possible unexplained differences in the three surveys.

4.5 Exclusion Restrictions

We include at least one exclusion restriction in each equation. To identify the credit demand model (equation 1), we make use of survey responses to the question "What is the most important problem facing your business today?", with possible answers distributed over 28 alternatives. One of these refers specifically to funding issues – "Cash flow". We account for this response using the dummy variable *Cash flow problem*. The logic of this variable can be thought of as resting on the theory of pecking order financing. Firms with internal funding problems are assumed to have a high demand for external financing (Myers and Majluf, 1984).

The source of identification in our credit application model (equation 2) comes from a variable *% purchased by trade credit*, which captures the percentage of purchases the firm makes using trade credit. Two mutually non-exclusive arguments back up the use of this variable. The first one is intuitive: if trade credit is a relatively expensive source of financing (compared to bank credit), firms that rely to a large extent on trade credit may be more inclined to apply for a bank loan. The second argument relies on the theoretical results of Biais and Gollier (1997), who argue that high reliance on trade credit from suppliers may signal firm quality in the sense that the firm is trusted by these suppliers; high-quality firms may, in turn, be less subject to discouragement. (The theory also implies that if this signal can be conveyed to a lender/bank, then high reliance on trade credit may also increase the probability of loan approval, by reducing adverse selection.)

The source of unique variation in the approval model (equation 3) comes from a single dummy variable, indicating if ownership of the firm has transferred at some point since it was founded, previously used by Levenson and Willard (2000). The reasoning is that firms for which a transfer of ownership has taken place, and which are still in business, should be more viable. Consequently, ownership transfer signals firm quality, which should positively affect the probability of approval, conditional on applying (but should be uncorrelated with the application as such). Note that also the loan, lender and relationship characteristics included in the approval equation provides additional sources of variation vis-à-vis the previous stages in the selection process.

[13]New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific.

Identification in the final instrumental variables estimation of loan size rationing is a key concern. The objective is to find a set of instruments that provide sufficient unique variation – after controlling for all firm, owner, relationship and loan/lender characteristics – to predict *both* collateral and loan interest rates, but which at the same time do not directly determine loan size rationing. This is a challenge.[14] We consider the following candidate instruments drawn from previous literature as well as based more on general economic reasoning.

For the loan rates, we consider two primary candidates. The first instrument is a simple dummy variable indicating if the loan interest rate is floating. Results of several previous studies (Berger and Udell, 1990; Brick and Palia, 2007; Chakravarty and Yilmazer, 2009; Cowling, 2010) indicate that the interest cost of floating-rate loans is lower than on fixed-rate loans, but the premium charged by banks for assuming the interest rate risk is unlikely to directly predict rationing (or other loan terms), suggesting that the floating-rate indicator may be a unique source of variation in the loan spread. The second instrument is the average yield on 10-year U.S. Treasury bonds in the month when the loan was approved (sourced from the Federal Reserve's website). We do not match maturities precisely (the average loan maturity in the sample is approximately 5 years).

For collateral, we construct two variables. The first is the dummy variable *Existing collateral*, which equals 1 when collateral and/or guarantees were pledged on outstanding loans. This variable can be considered as a proxy of collateral availability. Since existing loans tie up the pledged assets, they may use up collateral capacity, which may affect the likelihood of collateralization but is unlikely to affect the lender's decision to restrict credit if the loan is *not* collateralized (i.e., the only effect on rationing is the indirect one, via collateral on the most recent loan). Collateral on existing loans may also capture the firm's revealed preference for pledging collateral, which is likely to affect the probability of collateralization, but should not directly affect the lender's rationing decision (for given likelihood to require collateral). For the second variable we make use of the time series of the net percentage of banks tightening collateral requirements from the Federal Reserve's Senior Loan Officer Opinion Survey (SLOOS).

Both Treasury yields and the SLOOS data are pure time series (at quarterly frequency in the case of the SLOOS) and do not provide any cross-sectional variation as such, but since we observe the date at which a loan was contracted and the surveys cover loans contracted over three different time periods of more than three years' duration each, the time variation in these variables indirectly provides a great deal of variation also over the cross section of approved loans.

[14] Our estimation approach relies on the assumption that the maturity of the loan is more likely to be driven by exogenous preferences, or – at a minimum – that collateral requirements, loan interest rate and relative loan amount granted are more likely to be set for given maturity than the other way around.

4.6 Descriptive Statistics

Basic descriptive statistics, in the form of by-subsample means, standard deviations and univariate difference tests of the included variables, are presented in Table 1. The table also shows the extent of sample truncation at each stage in the analysis. Of the total sample (11,503 observations), roughly 46 percent are identified as having a non-zero credit demand. Of these, about 28 percent are "truly discouraged borrowers" (Jappelli, 1990), that never make any loan application. Among the 3,785 firms that do apply, only about 15 percent are turned down completely (i.e., are quantity-rationed), leaving 3,213 firms for the final instrumental-variables estimation, 9.5 percent of which are loan size rationed.

Panel A splits the sample into two groups, those firms that have demand for credit and those who do not need credit. Differences between these two groups are apparent when one considers firm and relationship characteristics. The univariate comparison shows that, on average, credit demand firms are younger, less profitable and riskier than non-demand firms. But when it comes to firm size (measured both by the total sales and the number of employees), credit demand firms are larger than non-credit seekers. They also have, on average, more lending relationships.

Panel B further divides the sample of firms with credit demand into two groups, applicant and non-applicant firms. We observe that applicant firms are considerably larger (measured by the total sales and the number of employees) and older on average than non-applicant firms, suggesting that smaller and younger firms are more likely to be discouraged. Similarly, a lower proportion of applicant firms has a history of bankruptcy or delinquency.

In terms of personal characteristics, owners of applicant firms are older, more experienced, and are more likely to have a college degree compared to non-applicant owners, suggesting that owners with lower levels of human capital may be discouraged from submitting a loan application. We also observe that a higher proportion of non-applicant firms have Asian, African American or Hispanic owners, possibly reflecting that minority business owners have an expectation of discrimination in the credit market. However, this result could also reflect self-rationing (self-screening) due to socio-economic factors, as these groups tend to have lower education and income levels. Similarly, while the lower proportion of female ownership for applying firms may be due to expectations of gender discrimination, female owners tend to have lower levels of human capital (Boden and Nucci, 2000; Fairlie and Robb, 2009) and lower sales turnover, job creation and profitability (Rosa et al., 1996).

In line with expectation, the unconditional mean comparison also shows that applicant firms entertain a larger number of financial service providers compared to non-applicant firms. Applicant firms also report considerably higher percentage of purchases made by trade credit.

Table 1. Univariate Analysis: Credit demand, Applied, Approved and Full amount granted firms

This table presents a univariate analysis of the means of the variables used in this study. Columns [1] and [2] present the means and standard deviations (in the bracket) of the variables for firms with credit demand and those who do not need credit, respectively; column [3] displays the difference in means of the variables presented in the first two columns. Columns [4] and [5] report the means and standard deviations of the variables for credit applicant and non-applicant firms, respectively; the difference in means of the variables between these two groups is reported in column [6]. Columns [7] and [8] present the means and standard deviations of the variables for approved and non-approved firms, respectively; column [9] displays the difference in means of the variables between these two groups of firms. While the means and standard deviations of the variables for full amount granted and loan size rationed firms are presented in columns [10] and [11], the difference in means of the variables between these two groups is displayed in column [12]. The t test of the statistical significance of the differences in means is indicated by asterisk, where ***, **, and * indicate significance at the 1% level, the 5% level and the 10% level, respectively.

	Demand [N = 7,650]			Applied [N = 2,915]			Approved [N = 2,030]			Full amt granted [N = 1,750]		
	Demand=1 [N = 2,915] [1]	Demand=0 [N = 4,735] [2]	[3=1-2]	Applied=1 [N = 2,030] [4]	Applied=0 [N = 885] [5]	[6=4-5]	Approved=1 [n = 1,750] [7]	Approved=0 [N = 280] [8]	[9=7-8]	Full amt Granted=1 [N = 1,624] [10]	Full amt Granted=0 [N = 126] [11]	[12 = 10 -11]
Total sales	4.728	3.466	1.262***	6.205	0.894	5.312***	7.064	1.381	5.683***	7.103	6.693	0.410
	(13.75)	(12.96)	(0.250)	(15.80)	(3.386)	(0.417)	(16.86)	(5.265)	(0.711)	(16.99)	(15.65)	(1.016)
Number of employees	37.20	25.76	11.441***	46.92	11.98	34.931***	52.08	17.92	34.156***	51.74	55.30	−3.555
	(65.87)	(53.38)	(1.112)	(72.58)	(32.39)	(1.972)	(76.08)	(36.86)	(3.247)	(75.47)	(81.76)	(4.586)
Firm age	14.19	16.45	−2.259***	15.39	11.10	4.292***	16.17	11.01	5.153***	16.23	15.54	0.696
	(12.33)	(13.11)	(0.239)	(13.13)	(9.261)	(0.375)	(13.53)	(9.532)	(0.590)	(13.52)	(13.64)	(0.816)
Profitability	0.124	0.179	−0.055***	0.118	0.142	−0.024*	0.117	0.122	−0.005	0.116	0.121	−0.005
	(0.347)	(0.390)	(0.007)	(0.304)	(0.439)	(0.011)	(0.286)	(0.393)	(0.014)	(0.286)	(0.285)	(0.017)
Leverage	3.709	1.622	2.087***	3.822	3.387	0.435	3.756	4.208	−0.452	3.542	5.778	−2.235*
	(14.86)	(10.01)	(0.246)	(14.88)	(14.81)	(0.488)	(14.88)	(14.85)	(0.704)	(14.43)	(18.53)	(0.915)
Firm default history	0.277	0.0982	0.178***	0.244	0.361	−0.118***	0.210	0.432	−0.221***	0.203	0.280	−0.076**
	(0.447)	(0.298)	(0.007)	(0.429)	(0.481)	(0.014)	(0.408)	(0.496)	(0.019)	(0.402)	(0.450)	(0.025)
Low diversification	0.575	0.677	−0.102***	0.541	0.661	−0.120***	0.533	0.591	−0.058**	0.539	0.470	0.069*
	(0.494)	(0.468)	(0.009)	(0.498)	(0.473)	(0.015)	(0.499)	(0.492)	(0.023)	(0.499)	(0.500)	(0.030)
Owner age				49.93	48.04	1.892***	50.37	47.44	2.939***	50.41	50.02	0.392
				(10.66)	(10.43)	(0.327)	(10.61)	(10.64)	(0.482)	(10.56)	(11.02)	(0.641)
Asian ownership				0.0438	0.0652	−0.021**	0.0398	0.0664	−0.027**	0.0388	0.0495	−0.011
				(0.205)	(0.247)	(0.007)	(0.196)	(0.249)	(0.009)	(0.193)	(0.217)	(0.012)
AfrAm ownership				0.0720	0.177	−0.104***	0.0432	0.233	−0.189***	0.0391	0.0825	−0.043***
				(0.259)	(0.381)	(0.009)	(0.203)	(0.423)	(0.011)	(0.194)	(0.276)	(0.012)
Hispanic ownership				0.0510	0.104	−0.053***	0.0445	0.0874	−0.043***	0.0447	0.0429	0.002
				(0.220)	(0.305)	(0.008)	(0.206)	(0.283)	(0.010)	(0.207)	(0.203)	(0.012)
Female ownership				0.156	0.271	−0.114***	0.144	0.227	−0.084***	0.145	0.129	0.016
				(0.363)	(0.444)	(0.012)	(0.351)	(0.419)	(0.016)	(0.352)	(0.335)	(0.021)

Table 1. Univariate Analysis: Credit demand, Applied, Approved and Full amount granted firms

This table presents a univariate analysis of the means of the variables used in this study. Columns [1] and [2] present the means and standard deviations (in the bracket) of the variables for firms with credit demand and those who do not need credit, respectively; column [3] displays the difference in means of the variables presented in the first two columns. Columns [4] and [5] report the means and standard deviations of the variables for credit applicant and non-applicant firms, respectively; the difference in means of the variables between these two groups is reported in column [6]. Columns [7] and [8] present the means and standard deviations of the variables for approved and non-approved firms, respectively; column [9] displays the difference in means of the variables between these two groups of firms. While the means and standard deviations of the variables for full amount granted and loan size rationed firms are presented in columns [10] and [11], the difference in means of the variables between these two groups is displayed in column [12]. The t test of the statistical significance of the differences in means is indicated by asterisk, where ***, **, and * indicate significance at the 1% level, the 5% level and the 10% level, respectively.

	Demand [N = 7,650]			Applied [N = 2,915]			Approved [N = 2,030]			Full amt granted [N = 1,750]		
	Demand=1 [N = 2,915] [1]	Demand=0 [N = 4,735] [2]	[3=1-2]	Applied=1 [N = 2,030] [4]	Applied=0 [N = 885] [5]	[6=4-5]	Approved=1 [n = 1,750] [7]	Approved=0 [N = 280] [8]	[9=7-8]	Full amt Granted=1 [N = 1,624] [10]	Full amt Granted=0 [N = 126] [11]	[12 = 10 -11]
Owner experience				19.93	16.28	3.651***	20.50	16.73	3.778***	20.51	20.40	0.119
				(10.81)	(10.28)	(0.329)	(10.84)	(10.08)	(0.487)	(10.75)	(11.72)	(0.655)
College				0.531	0.426	0.105***	0.549	0.430	0.119***	0.546	0.578	−0.032
				(0.499)	(0.495)	(0.015)	(0.498)	(0.496)	(0.023)	(0.498)	(0.495)	(0.030)
Owner share				71.04	84.23	−13.193***	69.52	79.51	−9.993***	69.74	67.41	2.328
				(29.25)	(24.21)	(0.862)	(29.52)	(26.15)	(1.318)	(29.53)	(29.41)	(1.782)
Owner default history				0.141	0.364	−0.223***	0.0989	0.378	−0.279***	0.0969	0.119	−0.022
				(0.348)	(0.481)	(0.012)	(0.299)	(0.485)	(0.015)	(0.296)	(0.324)	(0.018)
Number of sources	4.080	3.109	0.971***	4.593	2.746	1.848***	4.820	3.320	1.500***	4.828	4.747	0.081
	(2.151)	(1.948)	(0.038)	(2.081)	(1.712)	(0.061)	(2.048)	(1.786)	(0.091)	(2.051)	(2.027)	(0.123)
Relationship length							7.614	5.320	2.294***	7.711	6.678	1.033
							(9.003)	(6.645)	(0.396)	(8.998)	(9.014)	(0.544)
Distance							84.93	58.47	26.466*	84.53	88.83	−4.308
							(297.3)	(252.9)	(13.272)	(292.9)	(337.4)	(17.979)
Referral										0.0437	0.0625	−0.019
										(0.204)	(0.242)	(0.013)
Previous loan										0.0553	0.0493	0.006
										(0.229)	(0.217)	(0.014)
Primary bank										0.313	0.280	0.034
										(0.464)	(0.450)	(0.028)
Amount requested							0.917	0.219	0.698***	0.895	1.124	−0.229
							(4.130)	(0.992)	(0.174)	(4.125)	(4.177)	(0.249)
Maturity										49.36	52.07	−2.713
										(60.74)	(62.12)	(3.681)

Table 1. Univariate Analysis: Credit demand, Applied, Approved and Full amount granted firms

This table presents a univariate analysis of the means of the variables used in this study. Columns [1] and [2] present the means and standard deviations (in the bracket) of the variables for firms with credit demand and those who do not need credit, respectively; column [3] displays the difference in means of the variables presented in the first two columns. Columns [4] and [5] report the means and standard deviations of the variables for credit applicant and non-applicant firms, respectively; the difference in means of the variables between these two groups is reported in column [6]. Columns [7] and [8] present the means and standard deviations of the variables for approved and non-approved firms, respectively; column [9] displays the difference in means of the variables between these two groups of firms. While the means and standard deviations of the variables for full amount granted and loan size rationed firms are presented in columns [10] and [11], the difference in means of the variables between these two groups is displayed in column [12]. The t test of the statistical significance of the differences in means is indicated by asterisk, where ***, **, and * indicate significance at the 1% level, the 5% level and the 10% level, respectively.

	Demand [N = 7,650]			Applied [N = 2,915]			Approved [N = 2,030]			Full amt granted [N = 1,750]		
	Demand=1 [N = 2,915] [1]	Demand=0 [N = 4,735] [2]	[3=1-2]	Applied=1 [N = 2,030] [4]	Applied=0 [N = 885] [5]	[6=4-5]	Approved=1 [n = 1,750] [7]	Approved=0 [N = 280] [8]	[9=7-8]	Full amt Granted=1 [N = 1,624] [10]	Full amt Granted=0 [N = 126] [11]	[12 = 10 -11]
Collateral										0.843	0.836	0.007
										(0.364)	(0.371)	(0.022)
#collateral types										1.513	1.724	−0.211**
										(1.206)	(1.410)	(0.074)
Interest rate										7.915	8.197	−0.282
										(2.590)	(2.648)	(0.156)
Metropolitan area	0.787	0.790	−0.003	0.769	0.833	−0.065***	0.755	0.843	−0.087***	0.752	0.786	−0.034
	(0.410)	(0.408)	(0.008)	(0.422)	(0.373)	(0.013)	(0.430)	(0.364)	(0.019)	(0.432)	(0.411)	(0.026)
Banking concentration				0.506	0.461	0.045**	0.509	0.491	0.018	0.512	0.485	0.027
				(0.500)	(0.499)	(0.015)	(0.500)	(0.500)	(0.023)	(0.500)	(0.501)	(0.030)
Cash flow problem	0.151	0.153	−0.003									
	(0.358)	(0.360)	(0.007)									
% purch. trade credit				75.97	62.13	12.891***						
				(29.53)	(33.49)	(1.546)						
Owner transfer							0.335	0.210	0.125***			
							(0.472)	(0.408)	(0.021)			
Existing collateral										0.790	0.757	0.034
										(0.407)	(0.430)	(0.025)
Float rate										0.478	0.503	−0.025
										(0.500)	(0.501)	(0.030)

Panel C sorts the sample of applicant firms into two categories, approved and denied (quantity-rationed) firms. The reported mean differences in terms of basic firm, owner and relationship characteristics largely mimic those between applicant and non-applicant firms. Borrowers whose loan applications are approved are larger (measured by the total sales and the number of employees) and older compared to those whose applications turned down. Regarding demographics, owners of approved firms are older, more experienced, and are more likely to have a college degree, signaling that lenders may put weight on the human capital of the business owners. We also observe that approved firms have lower incidence of African American and Hispanic ownership than denied firms. Regarding lending relationships, firms whose loan applications are approved have longer and a larger number of relationships, and have a closer geographical proximity to their lenders compared to those whose applications are rejected. A lower proportion of approved firms have their headquarters located in metropolitan areas. Firms for which at least one ownership transfer has taken place are on average more likely to be approved for loans, in line with expectation.

Panel D, finally, classifies the sub-sample of approved firms into loan-size-rationed and full-amount-granted groups. Unconditional mean comparisons show that differences across these groups are markedly smaller than at previous stages. Rationed firms are about 20 percent younger. They also on average have significantly *lower* leverage (at less than 1/3 of that of non-rationed firms), but due to very high variance of the debt/equity ratio, this difference is significant only at the 10 percent level. The same goes for the 25 percent longer duration of the relationship with the lender of size-rationed firms. We see no systematic differences in either collateral use in general (about 60 percent of both rationed and non-rationed loans are collateralized), or in the number of collateral types pledged.

5. Regression Results

5.1 Benchmark Results

To determine whether collateral plays an independent role in helping reduce rationing in small business lending, we start by running simple, single-equation regressions of the main final-stage equation of loan size rationing to provide a "benchmark" with which to compare our final estimation. In this baseline model, a type of model that has traditionally been estimated, no corrections have been made, either for sample selection bias or for endogenously determined loan terms. The results are reported in Table 2. The estimated coefficients are obtained by running weighted regressions using the SSBF sampling weights.

Table 2. Benchmark Results: Collateral Effects on Loan-Size Rationing

This table presents the benchmark results of collateral effects on loan size rationing using a single-equation model. The dependent variable *Loan size rationing* takes the value one if the loan amount granted is less than the amount applied for, and zero otherwise; *Proportion rationed* is defined as one minus the proportion of the loan amount granted (i.e., the supplied loan mount divided by the demanded loan amount). The independent variable of interest *Collateral* takes unit value if collateral or guarantee was required to secure a loan, and is equal to zero for unsecured loans; *# collateral types* reflects the number of different types of collateral (including any guarantee) that were used to secure a loan. Columns (1) and (2) report the results of ordinary least square (OLS) regression using as dependent the dummy variable *Loan size rationing*, and they differ only in the way that collateral is measured. Columns (3) and (4) display the results from the probit models estimating the effects of collateral on the probability of being loan size rationed, and also differ only in the way that collateral is measured. The results of tobit regressions using as dependent the truncated variable *Proportion rationed* are presented in columns (5) and (6). The estimated coefficients are obtained by running weighted regressions using the SSBF sampling weights, and standard errors are heteroskedasticity robust. The t-test of significance is: *** significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.

	Loan size rationing								*Proportion rationed*			
	OLS				Probit				Tobit			
	(1)		(2)		(3)		(4)		(5)		(6)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Collateral variables												
Collateral	−0.034	(0.021)			−0.228*	(0.125)			−0.133*	(0.074)		
#collateral types			−0.000	(0.007)			−0.001	(0.040)			−0.005	(0.023)
Firm characteristics												
Log(Total sales)	−0.003	(0.009)	−0.004	(0.009)	−0.022	(0.053)	−0.025	(0.053)	−0.025	(0.034)	−0.027	(0.034)
Log(Number of employees)	−0.001	(0.010)	−0.000	(0.010)	−0.011	(0.060)	−0.008	(0.060)	0.009	(0.036)	0.012	(0.036)
Log(Firm age)	0.001	(0.010)	0.001	(0.010)	0.018	(0.066)	0.019	(0.065)	0.004	(0.037)	0.004	(0.037)
Profitability	0.005	(0.025)	0.008	(0.025)	0.048	(0.163)	0.066	(0.163)	0.053	(0.094)	0.063	(0.095)
Leverage	0.001	(0.001)	0.001	(0.001)	0.003	(0.003)	0.003	(0.003)	0.001	(0.001)	0.001	(0.001)
Firm default history	0.042**	(0.020)	0.042**	(0.020)	0.294***	(0.113)	0.292***	(0.113)	0.169**	(0.067)	0.168**	(0.067)
Low diversification	−0.002	(0.015)	−0.001	(0.015)	0.006	(0.094)	0.011	(0.093)	0.006	(0.059)	0.010	(0.058)
Owner characteristics												
Log(Owner age)	0.033	(0.046)	0.037	(0.046)	0.274	(0.275)	0.293	(0.276)	0.236	(0.166)	0.246	(0.167)
Asian ownership	0.055	(0.046)	0.057	(0.046)	0.265	(0.198)	0.264	(0.197)	0.144	(0.112)	0.142	(0.112)
AfrAm ownership	0.006	(0.033)	0.009	(0.032)	0.032	(0.195)	0.039	(0.193)	0.020	(0.115)	0.023	(0.114)
Hispanic ownership	−0.028	(0.031)	−0.027	(0.031)	−0.157	(0.214)	−0.154	(0.214)	−0.099	(0.120)	−0.097	(0.120)
Female ownership	−0.031*	(0.017)	−0.028*	(0.017)	−0.245**	(0.122)	−0.228*	(0.120)	−0.168**	(0.072)	−0.158**	(0.072)
Log(1 + Owner experience)	−0.016	(0.017)	−0.017	(0.017)	−0.134	(0.100)	−0.137	(0.099)	−0.099	(0.061)	−0.100*	(0.061)
College	0.005	(0.016)	0.005	(0.017)	0.027	(0.102)	0.030	(0.101)	−0.006	(0.060)	−0.003	(0.060)
Owner share	−0.000	(0.000)	−0.000	(0.000)	−0.002	(0.002)	−0.002	(0.002)	−0.001	(0.001)	−0.001	(0.001)
Owner default history	−0.012	(0.024)	−0.014	(0.024)	−0.108	(0.149)	−0.106	(0.151)	−0.049	(0.092)	−0.047	(0.093)
Relationship characteristics												
Number of sources	0.001	(0.005)	0.001	(0.005)	0.013	(0.029)	0.009	(0.029)	0.013	(0.017)	0.011	(0.017)

Table 2. Benchmark Results: Collateral Effects on Loan-Size Rationing

This table presents the benchmark results of collateral effects on loan size rationing using a single-equation model. The dependent variable *Loan size rationing* takes the value one if the loan amount granted is less than the amount applied for, and zero otherwise; *Proportion rationed* is defined as one minus the proportion of the loan amount granted (i.e., the supplied loan mount divided by the demanded loan amount). The independent variable of interest *Collateral* takes unit value if collateral or guarantee was required to secure a loan, and is equal to zero for unsecured loans; *# collateral types* reflects the number of different types of collateral (including any guarantee) that were used to secure a loan. Columns (1) and (2) report the results of ordinary least square (OLS) regression using as dependent the dummy variable *Loan size rationing*, and they differ only in the way that collateral is measured. Columns (3) and (4) display the results from the probit models estimating the effects of collateral on the probability of being loan size rationed, and also differ only in the way that collateral is measured. The results of tobit regressions using as dependent the truncated variable *Proportion rationed* are presented in columns (5) and (6). The estimated coefficients are obtained by running weighted regressions using the SSBF sampling weights, and standard errors are heteroskedasticity robust. The t-test of significance is: *** significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.

	Loan size rationing								*Proportion rationed*			
	OLS				Probit				Tobit			
	(1)		(2)		(3)		(4)		(5)		(6)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Log(1 + Relationship length)	−0.008	(0.008)	−0.007	(0.008)	−0.058	(0.054)	−0.053	(0.054)	−0.034	(0.032)	−0.031	(0.032)
Log(1 + Distance)	0.009*	(0.005)	0.009*	(0.005)	0.047*	(0.028)	0.049*	(0.029)	0.025	(0.017)	0.026	(0.017)
Referral	0.012	(0.035)	0.014	(0.035)	0.103	(0.197)	0.107	(0.196)	0.073	(0.119)	0.075	(0.119)
Previous loan	−0.023	(0.027)	−0.024	(0.027)	−0.156	(0.189)	−0.167	(0.187)	−0.077	(0.112)	−0.083	(0.111)
Lender characteristics												
Primary bank	−0.025	(0.016)	−0.024	(0.016)	−0.177	(0.109)	−0.178*	(0.108)	−0.104	(0.066)	−0.105	(0.066)
Loan characteristics												
Interest rate	−0.001	(0.003)	−0.001	(0.003)	−0.005	(0.019)	−0.002	(0.019)	−0.003	(0.012)	−0.002	(0.012)
Log(Maturity)	0.011	(0.008)	0.009	(0.008)	0.071	(0.050)	0.059	(0.049)	0.028	(0.030)	0.021	(0.029)
Amount / Total sales	0.001	(0.001)	0.001	(0.001)	0.005	(0.006)	0.004	(0.006)	0.002	(0.004)	0.002	(0.004)
Environmental factors												
Bank concentration	−0.013	(0.016)	−0.013	(0.016)	−0.058	(0.095)	−0.055	(0.095)	−0.045	(0.056)	−0.043	(0.057)
Metropolitan area	0.024	(0.015)	0.025	(0.015)	0.194*	(0.110)	0.194*	(0.110)	0.114*	(0.065)	0.114*	(0.065)
Loan type	*Yes*		*Yes*		*Yes*		*Yes*		*Yes*		*Yes*	
Lender type	*Yes*		*Yes*		*Yes*		*Yes*		*Yes*		*Yes*	
Organizational type	*Yes*		*Yes*		*Yes*		*Yes*		*Yes*		*Yes*	
Industry	*Yes*		*Yes*		*Yes*		*Yes*		*Yes*		*Yes*	
Region	*Yes*		*Yes*		*Yes*		*Yes*		*Yes*		*Yes*	
Survey	*Yes*		*Yes*		*Yes*		*Yes*		*Yes*		*Yes*	
R-squared	0.045		0.043									
N	2905		2905		2903		2903		2905		2905	

The results of ordinary least square (OLS) regressions using as dependent variable the dummy *Loan size rationing* are presented in columns 1 and 2 of Table 2. The two columns differ only in that collateral in the first column is measured by the simple dummy variable *Collateral*, and in second column as *#collateral types*. The probit models estimating the effects of collateral on the probability of being loan-size rationed are reported in columns 3 and 4, and also differ only in the way that collateral is measured. To examine the collateral effect on the magnitude of loan-size rationing, we estimate tobit regressions using as dependent variable the truncated variable *Proportion rationed* in columns 5 and 6.

As evident from the table, the estimations offer little evidence of the role of collateral in reducing loan size credit rationing. The coefficients on collateral are statistically insignificant in four, and significant at the 10 percent level in two regressions. Even the significant coefficients imply a relatively small effect of collateral on rationing. For example, the coefficient estimate of -0.228 in the probit model in column 3 corresponds to a marginal reduction of the probability of experiencing loan size credit rationing of approximately 9 percentage points when the loan contract includes collateral.[15] This weak result leaves open the question of whether collateral has an independent role in reducing credit rationing when other factors are controlled for.

The failure to establish a convincing empirical link supports our argument that results from a single-equation rationing model may be susceptible to potential biases. First, even size-rationed loans are approved loans. If collateral reduces also quantity rationing (and possibly also self-rationing), studying approved loans only will underestimate the effect of collateral for rationing in general (the selection bias). Second, if "riskier" firms are both more likely to use collateral and more likely to be rationed, as in the argument of Berger and Udell (1992) for instance, then there may be two opposing effects of collateral on rationing in single-equation models: a negative effect in line with standard theoretical predictions, and a positive effect stemming from the codetermination of collateral and rationing by (observed or unobserved) firm characteristics (the endogeneity bias).

As to the importance of control variables, the results show that only a few variables have a significant impact. In particular, coefficients for the variable capturing a firm's credit history are positive and highly significant in all regressions, suggesting that the probability of loan size rationing and the proportion of rationed amount increase for small businesses with bankruptcy or business delinquency track records, which is in accordance with expectation. Unlike what is generally perceived in the literature on gender discrimination, female business ownership tends to reduce the probability of rationing.[16] The marginally positive coefficient on *Distance* (in columns 1 through 4) is consistent with the geographic credit rationing theory. Moreover, the estimated coefficient on *Metropolitan area* is positive (and significant at the 10 percent

[15] Using the rule of thumb that probit coefficient estimates divided by 2.5 are a close approximation of the marginal effect on probability (Wooldridge, 2002).

[16] Note that the mean difference in the proportion of female owners is only 1.6 percentage points, and insignificant.

level), indicating that small businesses whose headquarters are located in the metropolitan areas are more likely to experience rationing.

In conclusion, we are unwilling to make too much of these results, given our argument that the estimations are likely to be flawed, due to both sample selection bias and endogeneity. These results are also comparable to those of previous studies only to a limit. The closest results are those of Kirschenmann (2016), who also estimates single-equation models of loan size rationing on firm, relationship and loan characteristics (including collateral), but where the difference is that Kirschenmann (2016) uses panel data, whereas our data is a pooled cross section with non-repeated observations for individual cross-section units, which precludes the possibility to control for unobserved firm heterogeneity. This is a potentially crucial difference, suggesting comparability is limited. Again, then, these results are intended only for comparison with our later results, where we perform estimations controlling for the influence of selectivity and endogeniety issues.

5.2 A trivariate probit selection model

As discussed earlier, our approach to dealing with the selectivity problem in the loan size rationing estimations is the three-step selection process, which is based on the assumption that credit demand, the propensity to apply for a loan, and the likelihood of being approved are a sequence of interrelated outcomes, necessitating joint estimation and allowing for error correlation. Table 3 reports the estimates of the trivariate probit regression.

The primary focus of this analysis is on the estimates of the correlation coefficients, which are reported at the bottom of Table 3. The estimated correlation coefficients are large and highly significant, supporting our basic premise that credit need, the firm's decision about whether to apply, and the lender's decision whether to approve are closely interrelated. Because the correlation terms take on positive values, the underlying latent variables that may explain these decisions tend to move together. For example, the latent variable that makes firms need credit may also induce them to make a loan application. One factor that influences a firm's application decision is the expectation that the firm maintains concerning the likelihood of approval/rejection. The positive value for the correlation term between application and approval suggests that the latent variable that influences this expectation also influences the lender's decision whether to approve the loan. In sum, the large positive values and significance of the correlation terms lend credence to the appropriateness of the framework of joint estimation using a trivariate probit model that explicitly accounts for the interrelated nature of the credit demand, application and approval decisions.

Table 3. A Trivariate Probit Selection Model: Demand, Application and Approval

This table presents results from a trivariate probit selection model. Column (1) displays results from a probit regression predicting credit demand (i.e., firms decide whether they need credit or not). Column (2) reports results from a probit regression predicting loan application (i.e., conditional on credit demand, firms decide whether to apply). Column (3) displays results from a probit regression predicting loan approval (i.e., given a firm's credit demand and application decision, lenders decide whether to approve). The estimated coefficients are obtained by running weighted regressions using the SSBF sampling weights, and standard errors are heteroskedasticity robust. The t-test of significance is: *** significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.

	Credit demand		Applied		Approved	
	(1)		(2)		(3)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
Log(Total sales)	−.025	(.015)	.058**	(.023)	.169***	(.041)
Log(Number of employees)	.029	(.022)	.031	(.029)	−.073	(.048)
Log(Firm age)	−.193***	(.020)	−.070**	(.032)	.149**	(.070)
Profitability	−.117***	(.044)	−.174***	(.057)	−.040	(.103)
Leverage	.003**	(.001)	.001	(.002)	.002	(.002)
Firm default history	.702***	(.046)	.280***	(.060)	−.335***	(.125)
Low diversification	−.069*	(.037)	−.064	(.046)	−.169**	(.077)
Log(Owner age)			−.220**	(.010)	.101	(.200)
Asian ownership			.021	(.078)	−.169	(.150)
AfrAm ownership			.044	(.068)	−.612***	(.141)
Hispanic ownership			−.109	(.078)	−.274**	(.133)
Female ownership			−.002	(.044)	−.085	(.090)
Log(1 + Owner Experience)			−.033	(.039)	−.184**	(.079)
College			.028	(.036)	.213***	(.080)
Primary owner share			−.001	(.001)	.000	(.002)
Owner default history			−.190***	(.050)	−.596***	(.099)
Number of sources	.197***	(.012)	.234	(.015)	.200***	(.032)
Log(1 + Relationship length)					.046	(.044)
Log(1 + Distance)					.017	(.023)
Amount / Total sales					.006	(.004)
Metropolitan area	−.078*	(.042)	−.208***	(.055)	−.371***	(.100)
Banking concentration			.003	(.036)	−.132*	(.079)
Cash flow problem	.125***	(.040)				
% purchase trade credit			.001**	(.001)		
Owner transfer					.059	(.085)
Loan type	*No*		*No*		*Yes*	
Lender type	*No*		*No*		*Yes*	
Organizational type	*Yes*		*Yes*		*Yes*	
Industry	*Yes*		*Yes*		*Yes*	
Region	*Yes*		*Yes*		*Yes*	
Survey	*Yes*		*Yes*		*Yes*	
Error correl., demand-appl.			.97***			
Error correl., demand-appr.					.54**	
Error correl., appl.-appr.					.51**	

a. Credit demand

Column 1 of Table 3 displays results from a probit regression estimating factors influencing small businesses demand for credit financing. The results show a high degree of correspondence with the univariate results depicted in Table 1, with the exception that firm size (measured as the total sales and the number of employees) appears to have no significant effect on credit demand. We observe that credit demand depends inversely on firm age. One explanation may be that older firms have access to alternative sources of financing; also, investment opportunities are typically thought to decline in firm age; hence older firms may seek less external financing.

The significantly positive coefficient on the variable identifying firms that list cash flow as a major problem indicates that firms that generate low (insufficient) cash flows desire more credit financing. This result accords well with the pecking order financing hypothesis. One could also apply a similar reasoning for the highly significant and negative coefficient on profitability, which suggests that profitable firms are less likely to demand credit, perhaps because they want to exhaust their internal funds. This result is consistent with the finding of Kayhan and Titman (2007) that more profitable firms tend to employ less credit financing. The result that less profitable firms are more likely to seek credit may suggest that adverse selection may be a potential problem. This view is supported by the positive and significant coefficient on leverage and the variable capturing a firm's bankruptcy or delinquency track records.

b. Loan application

Column 2 of Table 3 reports results from a probit regression estimating factors that influence a firm's decision whether to apply, given the firm's credit demand. The percentage purchased by trade credit has a positive and significant effect on the probability of loan application, so does firm size (measured by the total sales). We also observe that the probability of loan application is negatively associated with firm age. Profitability likewise decreases the likelihood of applying, whereas we find a highly significant and positive coefficient on the variable capturing a firm's default track record, consistent with an adverse selection explanation – that is, the self-selection of small businesses with a history of bankruptcy or delinquency, which may adversely affect the average quality of the application pool.

The conditional loan application effects of owner characteristics are substantially weaker than the univariate result tends to suggest. The only significant variables we find are owner age and the variable capturing the owner's past bankruptcy or delinquency, both negatively affecting the probability of a loan application. We interpret this finding along the line that older groups of small business owners and those with default records are more likely to be discouraged. This explanation is consistent with the finding of Han et al. (2009) that the probability of being discouraged is positively associated with owner age. After controlling for other key factors, we find no evidence that supports self-rationing on the basis of ethnic minorities.

Apart from the characteristics of the firm and its owner, the application decision also depends on relationships: the significantly positive coefficient on the number of sources of financial services suggests that firms with multiple relationships are less likely to be discouraged. This result is reasonable as firms can make repeated (and/or multiple) applications to different creditors. We also observe that firms whose headquarters are located in the metropolitan area are less likely to make a loan application.

c. Loan approval

Column 3 of Table 3 displays results from a probit regression predicting the lender's decision whether to approve the application or not, given the firm's credit demand and loan application decision. The coefficients on firm size and firm age are positive and significant. One could provide two plausible explanations for this result: first, firm size may be a reflection of success and availability of collateralizable assets; second, age could be a reflection of survival and information transparency (or reputational capital), making lenders more willing to approve loans. The significantly negative coefficient on the variable capturing a firm's credit history suggests that lenders place weight on previous default records, and are more likely to turn down loan applications of firms with the history of bankruptcy or delinquency.

The result also reveals that demographic characteristics of the owners influence the likelihood of being approved. Even after controlling for other key factors, we find evidence that minority ownership significantly reduces loan approval probability, as the coefficients on African American and Hispanic owners are significantly negative. In contrast, lenders do not appear to treat loan applicants differently on the basis of gender. Consistent with expectation, holding a college degree has a positive impact on the chances of loan approval. The negative coefficient on owner experience is, however, counterintuitive.

Aside from encouraging firms to submit their loan application, the number of sources of financial services also influences a lender's decision whether to approve the loan application. We also find some evidence that loan applications from concentrated banking markets tend to have lower likelihood of approval, suggesting that competitive banking markets increase access to credit for small businesses. Applications made from metropolitan areas also have lower approval rates.

5.3 Instrumental-Variables Estimation

Thus far we have shown that credit demand, application and approval are an interrelated sequential process, suggesting that the uncorrected results in Table 2 may be suffering from biases arising from non-random selection. To mitigate this concern, inverse Mill's ratios from the credit demand, loan application and approval equations are included in the final loan size rationing equation. In addition to the selectivity issues, collateral use may also be endogenously determined with other loan terms, potentially biasing coefficient estimates and confounding inference. To account for this effect, we estimate the loan size rationing equation using an instrumental variables approach.

5.3.1 Validity and Relevance of Instruments

The IV estimation method relies on the assumption that the excluded instruments are uncorrelated with the errors from the credit rationing equation, and that they are sufficiently correlated with the included endogenous variables (collateral and interest rates in our case). To ensure the validity and relevance of our instruments, we diagnose on the regression specification, and a representative set of the test statistics generated from the IV-GMM regression are presented in Table 4.

Table 4. Testing the Validity and Relevance of Instruments

This table presents test statistics and the corresponding p-values generated from IV-GMM regressions of the credit rationing equation 4. The test statistics reported in column (1) are generated when the included endogenous variables are *Collateral* and interest rates), and those displayed in column (2) are generated when the included endogenous variable are # *collateral types* and interest rates. *10% maximal IV relative bias* presents Stock and Yogo's (2005) critical values for the weak identification test based on the bias of the IV estimator relative to the bias of the OLS estimator.

	Collateral		*#collateral types*	
	(1)		(2)	
	Test statistic	P-value	Test statistic	P-value
Overidentification test				
Hansen J statistic	$\chi^2(2) = 0.819$	$P = 0.66$	$\chi^2(2) = 0.09$	$P = 0.96$
Underidentification test				
Kleibergen-Paap rk LM	$\chi^2(3) = 26.96$	$P = 0.00$	$\chi^2(3) = 25.57$	$P = 0.00$
Weak identification test				
Kleibergen-Paap Wald rk F	8.11		7.56	
10% maximal IV relative bias	7.56		7.56	
Weak-instrument-robust inference				
Anderson-Rubin Wald	$\chi^2(4) = 8.24$	$P = 0.08$	$\chi^2(4) = 8.24$	$P = 0.08$
Stock-Wright LM	$\chi^2(4) = 12.49$	$P = 0.01$	$\chi^2(4) = 12.49$	$P = 0.01$
Endogeneity test	$\chi^2(2) = 5.02$	$P = 0.08$	$\chi^2(2) = 7.77$	$P = 0.02$

Since our equation is overidentified by the order condition, the exogeneity assumption – that the exclusion restriction for the instruments are valid – can be tested using a test of overidentifying restrictions. When collateral is measured as a binary variable (the number of collateral types) the estimated Hansen's (1982) J statistic is 0.82 (0.09) with p-value of 0.66 (0.96). These insignificant statistics imply that the overidentification tests fail to reject the null hypothesis that the instruments are valid. The underidentification test – that the excluded instruments are relevant – is carried out using Kleibergen and Paap's (2006) rank LM statistic, which strongly rejects the null hypothesis that the excluded instruments are uncorrelated with the endogenous variables for both measures of collateral. We thus conclude that the chosen instruments are relevant.

We further test the strength of the instruments using "weak identification" tests. Since our results are heteroskedastic robust, the valid test statistic is the Kleibergen and Paap's (2006) rank Wald F-statistic. The row marked "10% maximal IV relative bias" contains Stock and Yogo's (2005) critical values for the tests that the instruments are not sufficiently correlated with the endogenous regressors based on the bias of the IV estimator relative to the bias of the OLS estimator. If we are willing to tolerate a 10% relative bias, we can conclude that our instruments are are not weak as the test statistics are equal to or above the critical value of 7.56. We also address the significance of the endogenous regressors in the structural equation being estimated, which we carry out using "weak instrument robust inference" tests. The test statistics for both Anderson and Rubin (1949) and Stock and Wright (2000) tests are significant. These tests reject the null hypothesis that the coefficients of the endogenous regressors are jointly equal to zero. Finally, the row marked "Endogeneity test" contains results for a test of the null hypothesis that the instrumented regressors can be treated as an endogenous variable, with interpretation in line with a standard Hausman test. The significant test statistics suggest that collateral and loan interest rate are jointly endogenous in the credit rationing equation, and that instrumental variable regression is the relevant approach.

5.3.2 IV-GMM and CUE Regression Results

Table 5 reports results from regressions that examine the impact of collateral on loan size rationing using instrumental variable estimation. The first two columns report the IV-GMM estimates on which the above identification tests are based, with corresponding first stage regressions for the instrumented variables in Appendix A. Column 1 shows that the estimated coefficient on the dummy variable *Collateral* is negative and statistically significant at the 5 percent level. Because it is a linear model, the magnitude of the coefficient suggests that pledging collateral reduces the probability of experiencing loan size rationing by about 15 percentage points. When collateral is measured by the number of the number of collateral types (column 2), we essentially get the same results; the coefficient on the variable *#collateral types* is negative and significant at 5 percent. The size of the coefficient suggests that pledging one additional type of collateral reduces the probability of experiencing loan size rationing by about 7 percentage points on the margin. This finding provides direct evidence that supports the information-asymmetry-based explanation of credit rationing and the mitigating role of collateral.

One potential concern with the results in columns 1-2 is that the instruments are not sufficiently strongly associated with the endogenous variables (cf. the weak identification tests), in which case the regular IV-GMM estimator may exhibit finite-sample bias (Stock et al., 2002). Columns 3-4 of Table 5 therefore report the results of the loan size rationing equation re-estimated using using the Continuously Updated Estimator (CUE) of (Hansen et al., 1996), as this estimation method shows better finite-sample properties than alternative IV/GMM procedures, especially in the presence of possible weak instruments (Baum et al., 2007). As can be noted from columns 3 and 4, the results remain essentially unchanged.

Only a few control variables turn out to have a statistically significant impact, although most variables have the expected sign. We note that the control variables that were significant in Table 2 (benchmark results) do not show a statistically significant impact, with the exception of metropolitan area, after controlling for selectivity and endogeneity effects. We find that firm size (measured by total sales) significantly reduces the probability of rationing, as does the duration of the firm-lender relationship. The finding that collateral, firm size, and the length of the firm-bank relationship are among the most important determinants of credit rationing suggests a strong case for explaining credit rationing in terms of lender-borrower information asymmetries.

Table 5. IV-GMM and CUE Regression Results

This table presents results from regressions that examine the impact of collateral on loan size rationing using instrumental variable estimation and controlling for selectivity issues. The dependent variable *Loan size rationing* takes the value one if the loan amount granted is less than the amount applied for, and zero otherwise. The independent variable of interest *Collateral* takes unit value if collateral or guarantee was required to secure a loan, and is equal to zero for unsecured loans; # *collateral types* reflects the number of different types of collateral (including any guarantee) that were used to secure a loan. Columns (1) and (2) report the IV-GMM estimates, and they differ only in the way that collateral is measured. Columns (3) and (4) display results from regressions estimated using the continuously updated estimator (CUE) of Hansen et al. (1996). The estimated coefficients are obtained by running weighted regressions using the SSBF sampling weights, and standard errors are heteroskedasticity robust. The t-test of significance is: *** significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.

	IV-GMM (Dep. var: rationing dummy)				CUE (Dep. var: rationing dummy)			
	(1)		(2)		(3)		(4)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Collateral variables								
Collateral	−0.151**	(0.076)			−0.152**	(0.077)		
#collateral types			−0.073**	(0.036)			−0.073**	(0.036)
Firm characteristics								
Log(Total sales)	−0.024**	(0.012)	−0.024*	(0.013)	−0.024*	(0.012)	−0.024*	(0.013)
Log(Number of employees)	0.014	(0.010)	0.016	(0.010)	0.014	(0.010)	0.016	(0.010)
Log(Firm age)	0.000	(0.020)	0.002	(0.020)	0.000	(0.020)	0.002	(0.020)
Profitability	−0.008	(0.037)	0.001	(0.040)	−0.009	(0.038)	0.001	(0.040)
Leverage	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)
Firm default history	0.033	(0.056)	0.040	(0.058)	0.033	(0.057)	0.040	(0.058)
Low diversification	0.011	(0.018)	0.007	(0.020)	0.011	(0.018)	0.007	(0.019)
Owner characteristics								
Log(Owner age)	−0.010	(0.060)	−0.023	(0.061)	−0.011	(0.060)	−0.023	(0.061)
Asian ownership	0.047	(0.053)	0.043	(0.053)	0.046	(0.052)	0.043	(0.053)
AfrAm ownership	0.068	(0.043)	0.073	(0.045)	0.068	(0.043)	0.073	(0.045)
Hispanic ownership	0.009	(0.041)	0.007	(0.043)	0.009	(0.041)	0.007	(0.043)
Female ownership	−0.024	(0.021)	−0.016	(0.021)	−0.024	(0.021)	−0.016	(0.021)
Log(1 + Owner experience)	0.000	(0.021)	−0.001	(0.022)	0.000	(0.021)	−0.001	(0.022)
College	−0.012	(0.020)	−0.012	(0.020)	−0.012	(0.020)	−0.012	(0.020)
Primary owner share	−0.000	(0.000)	−0.000	(0.000)	−0.000	(0.000)	−0.000	(0.000)
Owner default history	0.037	(0.039)	0.040	(0.041)	0.037	(0.039)	0.040	(0.041)
Relationship characteristics								
Number of sources	−0.024	(0.023)	−0.019	(0.024)	−0.024	(0.023)	−0.019	(0.024)
Log(1 + Relationship length)	−0.023**	(0.010)	−0.023**	(0.010)	−0.023**	(0.010)	−0.023**	(0.010)
Log(1 + Distance)	0.009	(0.006)	0.009	(0.006)	0.009	(0.006)	0.009	(0.006)
Referral	−0.013	(0.041)	−0.011	(0.043)	−0.013	(0.041)	−0.011	(0.043)
Previous loan	−0.007	(0.029)	−0.006	(0.031)	−0.007	(0.030)	−0.006	(0.031)

Table 5. IV-GMM and CUE Regression Results

This table presents results from regressions that examine the impact of collateral on loan size rationing using instrumental variable estimation and controlling for selectivity issues. The dependent variable *Loan size rationing* takes the value one if the loan amount granted is less than the amount applied for, and zero otherwise. The independent variable of interest *Collateral* takes unit value if collateral or guarantee was required to secure a loan, and is equal to zero for unsecured loans; *# collateral types* reflects the number of different types of collateral (including any guarantee) that were used to secure a loan. Columns (1) and (2) report the IV-GMM estimates, and they differ only in the way that collateral is measured. Columns (3) and (4) display results from regressions estimated using the continuously updated estimator (CUE) of Hansen et al. (1996). The estimated coefficients are obtained by running weighted regressions using the SSBF sampling weights, and standard errors are heteroskedasticity robust. The t-test of significance is: *** significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.

	IV-GMM (Dep. var: rationing dummy)				CUE (Dep. var: rationing dummy)			
	(1)		(2)		(3)		(4)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Lender characteristics								
Primary bank	−0.006	(0.018)	−0.003	(0.020)	−0.006	(0.019)	−0.003	(0.019)
Loan characteristics								
Interest rate	−0.020	(0.015)	−0.026*	(0.016)	−0.020	(0.015)	−0.026*	(0.016)
Log(Maturity)	0.006	(0.011)	0.004	(0.011)	0.006	(0.011)	0.004	(0.011)
Amount / Total sales	0.000	(0.002)	0.000	(0.002)	0.000	(0.002)	0.000	(0.002)
Environmental factors								
Bank concentration	0.010	(0.019)	0.017	(0.020)	0.010	(0.019)	0.017	(0.020)
Metropolitan area	0.058**	(0.026)	0.061**	(0.028)	0.058**	(0.026)	0.061**	(0.028)
Inverse Mills ratios								
Demand Mill's ratio	−0.069	(0.177)	−0.078	(0.179)	−0.069	(0.178)	−0.079	(0.179)
Applied Mill's ratio	−0.030	(0.181)	0.007	(0.183)	−0.030	(0.182)	0.007	(0.183)
Approval Mill's ratio	−0.176**	(0.076)	−0.193**	(0.079)	−0.176**	(0.076)	−0.193**	(0.079)
Loan type	*Yes*		*Yes*		*Yes*		*Yes*	
Lender type	*Yes*		*Yes*		*Yes*		*Yes*	
Organizational type	*Yes*		*Yes*		*Yes*		*Yes*	
Industry	*Yes*		*Yes*		*Yes*		*Yes*	
Region	*Yes*		*Yes*		*Yes*		*Yes*	
Survey	*Yes*		*Yes*		*Yes*		*Yes*	
N	2340		2340		2340		2340	

Turning to the inverse Mill's ratios, columns 1 through 4 show that the estimated coefficient on the inverse Mill's ratio from the approval equation is statistically significant at the 5 percent level, suggesting that the sample selection effect is non-trivial. The negative coefficient suggests that small businesses that have a high likelihood of approval are the ones that are less likely to experience loan size rationing. We also note that the inverse Mill's ratios from credit demand and application equations are statistically insignificant. One explanation for this could be that the selection effects from credit demand and loan application may already be contained in the selection effect from loan approval (note that the approval equation was estimated in Table 3 conditional on demand and application). Based on the significance of the inverse Mill's ratio, we can conclude that the uncorrected benchmark results in Table 2 could be, at least partially, due to selectivity bias.

5.3.3 IV-Probit and IV-Tobit Regression Results

As our measure of the dependent variable in columns 1 through 4 of Table 5 is a binary variable, we further examine the impact of collateral on rationing by estimating IV-probit regressions, to compare how the linear-probability-model results stack up against non-linear specifications of the rationing equation. We also estimate the determinants of the relative loan amount rationed (a truncated variable equal to zero for the majority of the sample) using IV-tobit and controlling for selection bias.

Column 1 of Table 6 displays results from IV-probit regression, where collateral is measured as a dummy variable; column 2 presents results where collateral is measured by the number of pledged assets. Consistent with the results reported in Table 5, we find a negative and significant impact of collateral. Also consistent with the Table 5 results is the finding that the other main determinants of rationing include firm size and the length of the firm-bank relationship, as well as a highly significant selection effect. As for the economic significance of the effect of collateral, the IV-probit estimates suggest a substantially larger impact than the IV-GMM estimates. For example, the coefficient estimate on the collateral dummy in column 1 is -0.982, suggesting that for firms that post collateral, the probability of loan size rationing is reduced by just below 40 percentage points on average. As previously, the coefficient estimate for the number of collateral types is roughly half that of the collateral dummy, suggesting in the IV-probit case that the reduction in the likelihood of rationing for each additional asset type pledged is on average on the order of 18 percentage points. In sum, the linear-probability estimates of the effect of collateral on rationing not only remain statistically significant, but the implied economic magnitude of the effect substantially increases when estimated by IV-probit.

Table 6. IV-Probit and IV-Tobit Regression Results

This table presents coefficient estimates from regressions that examine collateral effects on loan size rationing using instrumental variable estimation and controlling for selectivity issues. The dependent variable *Loan size rationing* takes the value one if the loan amount granted is less than the amount applied for, and zero otherwise; *Proportion rationed* is defined as one minus the proportion of the loan amount granted (i.e., the supplied loan amount divided by the demanded loan amount). *Collateral* takes unit value if collateral or guarantee was required to secure a loan, and zero for unsecured loans; # *collateral types* is the number of collateral types (including guarantees) that were used to secure a loan. Columns (1) and (2) report the results of IV-probit regressions using as a dependent variable *Loan size rationing*. Columns (3) and (4) display results from IV-tobit regressions using as a dependent variable *Proportion rationed*. The estimated coefficients are obtained by running weighted regressions using the SSBF sampling weights, and standard errors are heteroskedasticity robust. The t-test of significance is: *** significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.

	Loan size rationing				*Proportion rationed*			
	IV-Probit				IV-Tobit			
	(1)		(2)		(3)		(4)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Collateral variables								
Collateral	−0.982**	(0.429)			−0.540**	(0.267)		
#collateral types			−0.449***	(0.147)			−0.278**	(0.128)
Firm characteristics								
Log(Total sales)	−0.160**	(0.079)	−0.135*	(0.074)	−0.092*	(0.048)	−0.088*	(0.051)
Log(Number of employees	0.105	(0.065)	0.103*	(0.059)	0.073*	(0.039)	0.080**	(0.041)
Log(Firm age)	0.020	(0.119)	0.011	(0.108)	0.023	(0.072)	0.021	(0.075)
Profitability	0.015	(0.237)	0.010	(0.218)	0.013	(0.146)	0.011	(0.154)
Leverage	0.002	(0.003)	0.002	(0.003)	0.001	(0.002)	0.001	(0.002)
Firm default history	0.223	(0.321)	0.258	(0.294)	0.121	(0.199)	0.157	(0.208)
Low diversification	0.115	(0.115)	0.054	(0.109)	0.088	(0.072)	0.060	(0.077)
Owner characteristics								
Log(Owner age	0.009	(0.358)	−0.121	(0.318)	0.023	(0.216)	−0.057	(0.219)
Asian ownership	0.200	(0.243)	0.136	(0.217)	0.119	(0.141)	0.093	(0.144)
AfrAm ownership	0.381	(0.302)	0.398	(0.268)	0.286	(0.194)	0.327*	(0.198)
Hispanic ownership	0.098	(0.300)	0.043	(0.277)	0.053	(0.173)	0.025	(0.182)
Female ownership	−0.174	(0.136)	−0.118	(0.121)	−0.123	(0.081)	−0.102	(0.083)
Log(1 + Owner experience)	−0.047	(0.117)	−0.027	(0.108)	−0.060	(0.072)	−0.051	(0.075)
College	−0.104	(0.121)	−0.086	(0.110)	−0.096	(0.078)	−0.092	(0.081)
Primary owner share	−0.001	(0.002)	−0.000	(0.002)	−0.001	(0.001)	−0.001	(0.001)
Owner default history	0.169	(0.235)	0.200	(0.217)	0.066	(0.145)	0.097	(0.153)
Relationship characteristics								
Number of sources	−0.152	(0.136)	−0.091	(0.130)	−0.075	(0.077)	−0.051	(0.083)
Log(1 + Relationship length)	−0.169***	(0.057)	−0.150***	(0.052)	−0.112***	(0.035)	−0.113***	(0.037)

Table 6. IV-Probit and IV-Tobit Regression Results

This table presents coefficient estimates from regressions that examine collateral effects on loan size rationing using instrumental variable estimation and controlling for selectivity issues. The dependent variable *Loan size rationing* takes the value one if the loan amount granted is less than the amount applied for, and zero otherwise; *Proportion rationed* is defined as one minus the proportion of the loan amount granted (i.e., the supplied loan amount divided by the demanded loan amount). *Collateral* takes unit value if collateral or guarantee was required to secure a loan, and zero for unsecured loans; # *collateral types* is the number of collateral types (including guarantees) that were used to secure a loan. Columns (1) and (2) report the results of IV-probit regressions using as a dependent variable *Loan size rationing*. Columns (3) and (4) display results from IV-tobit regressions using as a dependent variable *Proportion rationed*. The estimated coefficients are obtained by running weighted regressions using the SSBF sampling weights, and standard errors are heteroskedasticity robust. The t-test of significance is: *** significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.

	Loan size rationing				*Proportion rationed*			
	IV-Probit				IV-Tobit			
	(1)		(2)		(3)		(4)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Log(1 + Distance)	0.048	(0.033)	0.050*	(0.030)	0.025	(0.021)	0.031	(0.022)
Referral	−0.041	(0.246)	−0.014	(0.230)	−0.042	(0.140)	−0.027	(0.149)
Previous loan	−0.031	(0.193)	−0.023	(0.182)	−0.023	(0.116)	−0.021	(0.124)
Lender characteristics								
Primary bank	−0.014	(0.119)	−0.018	(0.110)	−0.002	(0.073)	−0.005	(0.077)
Loan characteristics								
Interest rate	−0.084	(0.105)	−0.144	(0.090)	−0.061	(0.065)	−0.107	(0.069)
Log(Maturity)	0.042	(0.066)	0.028	(0.056)	−0.000	(0.038)	−0.006	(0.038)
Amount / Total sales	0.001	(0.007)	−0.000	(0.007)	−0.000	(0.005)	−0.001	(0.005)
Environmental factors								
Bank concentration	0.086	(0.115)	0.125	(0.105)	0.034	(0.068)	0.065	(0.073)
Metropolitan area	0.429**	(0.172)	0.363**	(0.165)	0.225**	(0.102)	0.217**	(0.108)
Inverse Mills ratios								
Demand Mill's ratio	−0.542	(1.025)	−0.472	(0.929)	−0.439	(0.638)	−0.466	(0.656)
Applied Mill's ratio	−0.091	(1.107)	0.187	(1.009)	0.089	(0.689)	0.266	(0.712)
Approval Mill's ratio	−1.253**	(0.555)	−1.214**	(0.516)	−0.732**	(0.365)	−0.807**	(0.373)
Loan type	*Yes*		*Yes*		*Yes*		*Yes*	
Lender type	*Yes*		*Yes*		*Yes*		*Yes*	
Organizational type	*Yes*		*Yes*		*Yes*		*Yes*	
Industry	*Yes*		*Yes*		*Yes*		*Yes*	
Region	*Yes*		*Yes*		*Yes*		*Yes*	
Survey	*Yes*		*Yes*		*Yes*		*Yes*	
Wald test	$\chi^2(2) = 4.03$	$P = 0.13$	$\chi^2(2) = 11.51$	0.00	$\chi^2(2) = 4.14$	$P = 0.13$	$\chi^2(2) = 11.19$	$P = 0.00$
N	2338		2338		2340		2340	

One final issue is whether pledging collateral also influences the magnitude of the rationed amount. In this complementary analysis, we estimate IV-tobit regressions by using as dependent variable the proportion of the applied-for amount rationed (one minus the proportion of the loan amount granted). Since the dependent variable is truncated between zero and one, the use of IV-tobit regression is more appropriate than alternative estimation methods. The results are reported in columns 3 and 4 of Table 6. The negative and statistically significant coefficient on *Collateral* in column 3 suggests that pledging collateral is associated not only with a reduction in the probability of experiencing loan size rationing, but also in the relative amount rationed. The negative and statistically significant coefficient on *#collateral types* suggests that an increase in the number of types of pledged assets also reduces the magnitude of the rationed amount. In sum, our finding provides direct empirical evidence of the role of collateral in mitigating both the probability of and the extent of loan size rationing.

7. Conclusion

There is a substantial body of theoretical work in the financial intermediation literature arguing that pledging collateral alleviates the information asymmetries that could lead to credit rationing. Yet, there is limited empirical research that establishes a direct link between posting collateral and credit rationing. The purpose of this study is to examine the empirical association between collateral and credit rationing in small business finance. To do that, we use survey data, which offers clean measures of credit rationing, and the focus of the analysis is on loan size rationing (the situation where a lender grants smaller loan amount than the borrower requested).

The sequential nature of the loan application/approval process, however, could become a potential source of selection bias if ignored. We estimate a three-step selection process to account for the potential selectivity problems. The findings show that the sequential loan demand, application and approval decisions are strongly related to one another. Prior literature also suggests that major loan terms are co-determined in credit contracting arrangements. To overcome the potential endogeneity bias arising from joint determination of loan terms, such as the pledged collateral and interest rate charged on the loans, we use instrumental variables estimation in the final loan size rationing models.

In benchmark regressions which do not account for potential selection and endogeneity bias, we find little evidence of an effect of collateral on rationing. In contrast, controlling for these issues we find consistent evidence of a direct empirical link between collateral and credit rationing, using several different IV estimators. More specifically, pledging collateral is associated with a reduction in the likelihood of experiencing loan-size credit rationing on the order of between 15 and 40 percentage points, depending on specification. Firms that pledge a large number of collateral types are also less likely to encounter credit rationing. The proportion of the loan amount rationed, defined as one less the proportion of the loan amount granted, is also observed to be negatively related to the incidence of collateral and the number of collateral types pledged.

REFERENCES

Anderson, T. W. and Rubin, H. (1949). Estimation of the parameters of a single equation in a complete system of stochastic equations. *Annals of Mathematical Statistics*, 20:46–63.

Ang, J. S., Lin, J. W., and Tyler, F. (1995). Evidence on the lack of separation between business and personal risks among small businesses. *Journal of Small Business Finance*, 4:197–210.

Atanasova, C. V. and Wilson, N. (2004). Disequilibrium in the UK corporate loan market. *Journal of Banking & Finance*, 28:595–614.

Avery, R. B., Bostic, R. W., and Samolyk, K. A. (1998). The role of personal wealth in small business finance. *Journal of Banking & Finance*, 22:1019–1061.

Baum, C. F., Schaffer, M. F., and Stillman, S. (2007). Enhanced routines for instrumental variables / generalized method of moments estimation and testing. *Stata Journal*, 7:465–506.

Becchetti, L., Garcia, M. M., and Trovato, G. (2011). Credit rationing and credit view: Empirical evidence from an ethical bank in Italy. *Journal of Money, Credit and Banking*, 43:1217–1245.

Benjamin, D. (1978). The use of collateral to enforce debt contracts. *Economic Inquiry*, 16:333–359.

Berger, A. N., Espinosa-Vega, M. A., Frame, W. S., and Miller, N. H. (2011a). Why do borrowers pledge collateral? New empirical evidence on the role of asymmetric information. *Journal of Financial Intermediation*, 20:55–70.

Berger, A. N., Frame, W. S., and Ioannidou, V. (2011b). Tests of ex ante versus ex post theories of collateral using private and public information. *Journal of Financial Economics*, 100:85–97.

Berger, A. N., Miller, N. H., Petersen, M. A., Rajan, R. G., and Stein, J. C. (2005). Does function follow organizational form? Evidence from the lending practices of large and small banks. *Journal of Financial Economics*, 76:237–269.

Berger, A. N. and Udell, G. F. (1990). Collateral, loan quality and bank risk. *Journal of Monetary Economics*, 25:21–42.

Berger, A. N. and Udell, G. F. (1992). Some evidence on the empirical significance of credit rationing. *Journal of Political Economy*, 100:1047–1077.

Berger, A. N. and Udell, G. F. (1995). Relationship lending and lines of credit in small firm finance. *Journal of Business*, 68:351–381.

Besanko, D. and Thakor, A. V. (1987). Collateral and rationing: Sorting equilibria in monopolistic and competitive credit markets. *International Economic Review*, 28:671–689.

Bester, H. (1985). Screening vs. rationing in credit markets with imperfect information. *American Economic Review*, 75:850–855.

Bester, H. (1987). The role of collateral in credit markets with imperfect information. *European Economic Review*, 31:887–899.

Beutler, T. and Grobéty, M. (2013). The collateral channel under imperfect debt enforcement. *Swiss National Bank Working Papers*.

Biais, B. . and Gollier, C. . (1997). Trade credit and credit rationing. *Review of Financial Studies*, 10:903–937.

Black, S. E. and Strahan, P. E. (2002). Entrepreneurship and bank credit availability. *Journal of Finance*, 57:2807–2833.

Blanchflower, D. G., Levine, P. B., and Zimmerman, D. J. (2003). Discrimination in the small-business credit market. *Review of Economics and Statistics*, 85:930–943.

Boden, R. J. J. and Nucci, A. R. (2000). On the survival prospects of men's and women's new business ventures. *Journal of Business Venturing*, 15:347–362.

Boot, A. W. (2000). Relationship banking: What do we know? *Journal of Financial Intermediation*, 9:7–25.

Boot, A. W., Thakor, A. V., and Udell, G. F. (1991). Secured lending and default risk: Equilibrium analysis, policy implications and empirical results. *Economic Journal*, 101:458–472.

Brick, I. E. and Palia, D. (2007). Evidence of jointness in the terms of relationship lending. *Journal of Financial Intermediation*, 16:452–476.

Carbo-Valverde, S., Degryse, H., and Rodríguez-Fernández, F. (2015). The impact of securitization on credit rationing: Empirical evidence. *Journal of Financial Stability*, 20:36–50.

Carter, S., Shaw, E., Lam, W., and Wilson, F. (2007). Gender, entrepreneurship, and bank lending: The criteria and processes used by bank loan officers in assessing applications. *Entrepreneurship Theory and Practice*, 31:427–444.

Cavalluzzo, K. and Wolken, J. (2005). Small business loan turndowns, personal wealth, and discrimination. *Journal of Small Business Finance*, 78:2153–2178.

Cavalluzzo, K. S., Cavalluzzo, L. C., and Wolken, J. D. (2002). Competition, small business financing, and discrimination: Evidence from a new survey. *Journal of Small Business Finance*, 75:641–679.

Cenni, S., Monferra, S., Salotti, V., Sangiorgi, M., and Torluccio, G. (2015). Credit rationing and relationship lending. Does firm size matter? *Journal of Banking & Finance*, 53:249–265.

Cerqueiro, G., Ongena, S., and Roszbach, K. (2016). Collateralization, bank loan rates, and monitoring. *Journal of Finance*, 71:1295–1322.

Chakraborty, A. and Hu, C. X. (2006). Lending relationships in line-of-credit and nonline-of-credit loans: Evidence from collateral use in small business. *Journal of Financial Intermediation*, 15:86–107.

Chakravarty, S. and Yilmazer, T. (2009). A multistage model of loans and the role of relationships. *Financial Management*, 38:781–816.

Chan, Y.-S. and Kanatas, G. (1985). Asymmetric valuation and the role of collateral in loan agreements. *Journal of Money, Credit and Banking*, 17:84–95.

Chan, Y.-S. and Thakor, A. V. (1987). Collateral and competitive equilibria with moral hazard and private information. *Journal of Finance*, 42:345–363.

Cheng, X. and Degryse, H. (2010). Information sharing and credit rationing: Evidence from the introduction of a public credit registry. *European Banking Center Discussion Paper No. 2010-07S*.

Coco, G. (2000). On the use of collateral. *Journal of Economic Surveys*, 14:191–214.

Cole, R. and Sokolyk, T. (2016). Who needs credit and who gets credit? evidence from the surveys of small business finances. *Journal of Financial Stability*, 24:46–60.

Cole, R. A. and Mehran, H. (2011). Gender and the availability of credit to privately held firms: Evidence from the surveys of small business finances. *FRB of New York Staff Report No. 383*.

Coleman, S. (2002). Borrowing patterns for small firms: A comparison by race and ethnicity. *Journal of Entrepreneurial Finance and Business Ventures*, 7:77–98.

Cowling, M. (1999). The incidence of loan collateralisation in small business lending contracts: Evidence from the UK. *Applied Economics Letters*, 6:291–293.

Cowling, M. (2010). The role of loan guarantee schemes in alleviating credit rationing in the uk. *Journal of Financial Stability*, 6:36–44.

Degryse, H. and Cayseele, P. V. (2000). Relationship lending within a bank-based system: Evidence from european small business data. *Journal of Financial Intermediation*, 9:90–109.

Diamond, D. W. (1989). Reputation acquisition in debt markets. *Journal of Political Economy*, 97:57–79.

Diamond, D. W. (1991). Monitoring and reputation: The choice between bank loans and directly placed debt. *Journal of Political Economy*, 99:689–721.

Drakos, K. and Giannakopoulos, N. (2011). On the determinants of credit rationing: Firm-level evidence from transition countries. *Journal of International Money and Finance*, 30:1773–1790.

Fairlie, R. W. and Robb, A. M. (2009). Gender differences in business performance: evidence from the characteristics of business owners survey. *Small Business Economics*, 33:375–395.

Freimer, M. and Gordon, M. J. (1965). Why bankers ration credit. *Quarterly Journal of Economics*, 79:397–416.

Gabriel, S. A. and Rosenthal, S. S. (1991). Credit rationing, race, and the mortgage market. *Journal of Urban Economics*, 29:371–379.

Han, L., Fraser, S., and Storey, D. J. (2009). Are good or bad borrowers discouraged from applying for loans? Evidence from US small business credit markets. *Journal of Banking & Finance*, 33:415–424.

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica*, 50:1029–1054.

Hansen, L. P., Heaton, J., and Yaron, A. (1996). Finite-sample properties of some alternative gmm estimators. *Journal of Business & Economic Statistics*, 14:262–280.

Harhoff, D. and Körting, T. (1998). Lending relationships in Germany - Empirical evidence from survey data. *Journal of Banking & Finance*, 22:1317–1353.

Haselman, R., Pistor, K., and Vig, V. (2010). How law affects lending. *Review of Financial Studies*, 23:549–580.

Hernández-Cánovas, G. and Martínez-Solano, P. (2006). Banking relationships: effects on debt terms for small spanish firms. *Journal of Small Business Management*, 44:315–333.

Hess, J. D. (1984). The use of collateral to enforce debt contracts: Profit maximization. *Economic Inquiry*, 24:349–356.

Inderst, R. and Müller, H. M. (2007). A lender-based theory of collateral. *Journal of Financial Economics*, 84:826–859.

Innes, R. D. (1990). Limited liability and incentive contracting with ex-ante choices. *Journal of Economic Theory*, 52:45–67.

Jaffee, D. M. and Modigliani, F. (1969). A theory and test of credit rationing. *American Economic Review*, 59:850–872.

Jaffee, D. M. and Russell, T. (1976). Imperfect information, uncertainty, and credit rationing. *Quarterly Journal of Economics*, 90:651–666.

Jappelli, T. (1990). Who is credit constrained in the U. S. economy? *Quarterly Journal of Economics*, 105:219–234.

Jiménez, G., Ongena, S., Peydró, J.-L., and Saurina, J. (2012). Credit supply and monetary policy: Identifying the bank balance-sheet channel with loan applications. *American Economic Review*, 102:2301–2326.

Jiménez, G., Salas, V., and Saurina, J. (2006). Determinants of collateral. *Journal of Financial Economics*, 81:255–282.

Kayhan, A. and Titman, S. (2007). Firms' histories and their capital structures. *Journal of Financial Economics*, 83:1–32.

Kirschenmann, K. (2016). Credit rationing in small firm-bank relationships. *Journal of Financial Intermediation*, 26:68–99.

Kjenstad, E. C., Su, X., and Zhang, L. (2002). Credit rationing by loan size: A synthesized model. *Quarterly Review of Economics and Finance*, 55:20–27.

Kleibergen, F. R. and Paap, R. (2006). Generalized reduced rank tests using the singular value decomposition. *Journal of Econometrics*, 133:97–126.

Kon, Y. and Storey, D. J. (2003). A theory of discouraged borrowers. *Small Business Economics*, 21:37–49.

Leeth, J. D. and Scott, J. A. (1989). The incidence of secured debt: Evidence from the small business community. *Journal of Financial and Quantitative Analysis*, 24:379–394.

Lehmann, E. and Neuberger, D. (2001). Do lending relationships matter? Evidence from survey data in Germany. *Journal of Economic Behavior and Organization*, 45:339–359.

Levenson, A. R. and Willard, K. L. (2000). Do firms get the financing they want? Measuring credit rationing experienced by small business in the US. *Small Business Economics*, 14:83–94.

Machauer, A. and Weber, M. (1998). Bank behavior based on internal credit ratings of borrowers. *Journal of Banking and Finance*, 22:1355–1383.

Manove, M., Padilla, A. J., and Pagano, M. (2001). Collateral versus project screening: A model of lazy banks. *RAND Journal of Economics*, 32:726–744.

Menkhoff, L., Neuberger, D., and Suwanaporn, C. (2006). Collateral-based lending in emerging markets: Evidence from Thailand. *Journal of Banking & Finance*, 30:1–21.

Mester, L. (1997). What's the point of credit scoring? *Journal of Political Economy*, pages 3–16.

Mester, L. J., Nakamura, L. I., and Renault, M. (2001). Checking accounts and bank monitoring. *FRB of Philadelphia Working Paper No. 01-3*.

Munnell, A., Tootell, G., Browne, L. E., and McEneaney, J. (1996). Mortgage lending in boston: Interpreting HMDA data. *Journal of Small Business Finance*, 86:25–53.

Myers, S. C. and Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, 13:187–221.

Ogawa, K. and Suzuki, K. (2000). Demand for bank loans and investment under borrowing constraints: A panel study of Japanese firm data. *Journal of the Japanese and International Economies*, 14:1–21.

Petersen, M. A. and Rajan, R. G. (1994). The benefits of lending relationships: Evidence from small business data. *Journal of Finance*, 49:3–37.

Puri, M., Rocholl, J., and Steffen, S. (2011). Global retail lending in the aftermath of the us financial crisis: Distinguishing between supply and demand effects. *Journal of Financial Economics*, 100:556–578.

Roodman, D. (2011). Fitting fully observed recursive mixed-process models with cmp. *The Stata Journal*, 11:159–206.

Rosa, P., Carter, S., and Hamilton, D. (1996). Gender as a determinant of small business performance: Insights from a British study. *Small Business Economics*, 8:463–478.

Schreft, S. L. and Villamil, A. P. (1992). Credit rationing by loan size in commercial loan markets. *Economic Review, Federal Reserve Bank of Richmond*, May:3–8.

Shen, C.-H. (2002). Credit rationing for bad companies in bad years: Evidence from bank loan transaction data. *Journal of Finance and Economics*, 7:261–278.

Steijvers, T. and Voordeckers, W. (2009). Collateral and credit rationing: A review of recent empirical studies as a guide for future research. *Journal of Economic Surveys*, 23:924–946.

Stiglitz, J. E. and Weiss, A. (1981). Credit rationing in markets with imperfect information. *American Economic Review*, 71:393–410.

Stiglitz, J. E. and Weiss, A. (1987). Credit rationing with many borrowers. *American Economic Review*, 77:228–231.

Stock, J. H. and Wright, J. H. (2000). Gmm with weak identification. *Journal of Econometrics*, 68:1055–1096.

Stock, J. H., Wright, J. H., and Yogo, M. (2002). A survey of weak instruments and weak identification in generalized method of moments. *Journal of Business & Economic Statistics*, 20:518–529.

Stock, J. H. and Yogo, M. (2005). Testing for weak instruments in linear iv regression. In Andrews, D. and Stock, J., editors, *Identification and Inference for Econometric Models: Essays in honor of Thomas Rothenberg*. Cambridge University Press, New York.

Voordeckers, W. and Steijvers, T. (2006). Business collateral and personal commitments in SME lending. *Journal of Banking & Finance*, 30:3067–3086.

Watson, H. (1984). Credit markets and borrower effort. *Southern Economic Journal*, 50:802–813.

Wooldridge, J. M. (2002). *Econometric Analysis of Cross Section and Panel Data*. MIT Press, Cambridge, Massachusetts.

Appendix A. First-stage results

Table 7. First stage regressions for endogenous variables

This table presents the IV-GMM first stage regression results for the included endogenous variables. *Collateral* takes unit value if collateral or guarantee was required to secure a loan, and is equal to zero for unsecured loans; # *collateral types* reflects the number of different types of collateral (including any guarantee) that were used to secure a loan. Column (1) reports results from the first stage for *Collateral*. Column (2) displays results from the first stage for *Interest rate*. Column (3) presents results from the first stage for # *collateral types*. The estimated coefficients are obtained by running weighted regressions using the SSBF sampling weights, and standard errors are heteroskedasticity robust. The t-test of significance is: *** significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.

	Collateral		*Interest rates*		*# collateral types*	
	(1)		(2)		(3)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
Existing collateral	.284***	.034	.037	.177	.544***	.079
% of banks tightening collateral	.002	.001	.031***	.010	.006	.004
Float rate	.041*	.025	−.527***	.150	.289***	.077
Treasury rate	.020	.016	.395***	.102	−.002	.049
Log(Total sales)	.023	.015	−.195*	.110	.076*	.045
Lot(Number of employees)	−.003	.016	.031	.083	.019	.045
Log(Firm age)	−.017	.026	−.055	.154	−.041	.066
Profitability	−.072*	.043	−.324	.247	−.074	.132
Leverage	.000	.001	−.003	.004	.002	.002
Firm default history	−.0309	.070	.279	.457	.045	.188
Low diversification	−.032	.023	−.042	.175	−.148**	.072
Log(owner age)	−.122*	.072	−.753	.489	−.391**	.187
Asian ownership	−.102	.062	.070	.274	−.267**	.126
Black ownership	.049	.071	1.125*	.573	.128	.156
Hispanic ownership	.016	.056	.285	.309	−.077	.128
Female ownership	−.058**	.029	−.123	.185	.002	.087
Log(1 + Owner experience)	.009	.024	−.015	.207	.037	.073
Collage	.016	.023	−.110	.150	.049	.076
Primary owner share	.000	.000	.002	.003	.002	.001
Owner default history	.039	.055	.408	.324	.106	.137
Number of sources	−.008	.027	.022	.177	.081	.074
Log(1 + Relationship length)	−.013	.013	−.060	.079	−.016	.037
Log(1 + distance)	.002	.007	.123**	.055	−.001	.018
Referral	−.077	.057	.349	.369	−.158	.123
Previous loan	−.007	.037	.208	.216	−.040	.120
Primary bank	−.018	.025	.385**	.189	−.087	.080
Log(Maturity)	.049***	.013	−.140	.090	.088***	.032
Amount / Total sales	.002**	.0017	−.024***	.006	.004	.003
Bank concentration	.014	.023	.423**	.172	.067	.074
Metropolitan area	−.039	.036	.101	.270	−.112	.104
Demand Mill's ratio	.004	.231	−.480	1.509	.074	.609
Applied Mill's ratio	−.002	.224	1.077	1.713	.453	.623
Approved Mill's ratio	.043	.113	−.993	.687	−.041	.297
Loan type	*Yes*		*Yes*		*Yes*	
Lender type	*Yes*		*Yes*		*Yes*	
Organizational type	*Yes*		*Yes*		*Yes*	
Industry	*Yes*		*Yes*		*Yes*	
Region	*Yes*		*Yes*		*Yes*	
Survey	*Yes*		*Yes*		*Yes*	
N	2340		2340		2340	

Does Collateral Reduce Loan-Size Credit Rationing? Survey Evidence

ALEMU TULU CHALA & JENS FORSSBÆCK

In theory, the use of collateral in credit contracting should mitigate the information problems that are widely held to be the primary cause of credit rationing. However, direct empirical evidence of the link between collateral use and credit rationing is scant. This paper examines the relationship between collateral and credit rationing using survey data that provides clean measures of quantity and loan size rationing. We find that selection problems arising from the loan application process and co-determination of loan terms significantly influence the link between collateral and rationing. Accounting for these problems, our results suggest that collateral reduces the likelihood of experiencing loan-size credit rationing by between 15 and 40 percentage points, and that collateral also decreases the relative loan amount rationed.

THE KNUT WICKSELL CENTRE FOR FINANCIAL STUDIES

The Knut Wicksell Centre for Financial Studies conducts cutting-edge research in financial economics and related academic disciplines. Established in 2011, the Centre is a collaboration between Lund University School of Economics and Management and the Research Institute of Industrial Economics (IFN) in Stockholm. The Centre supports research projects, arranges seminars, and organizes conferences. A key goal of the Centre is to foster interaction between academics, practitioners and students to better understand current topics related to financial markets.

LUND UNIVERSITY
School of Economics and Management

LUND UNIVERSITY
SCHOOL OF ECONOMICS AND MANAGEMENT
Working paper 2018:6
The Knut Wicksell Centre for Financial Studies