Learning-by-lending and learning-by-repaying: A two-sided learning model for defaults on Small Business Administration loans

Abstract

The two-sided endogenous learning in third-party guarantee loans between small business borrowers and bank branches remains less understood. Drawing on a sample of Small Business Administration (SBA) loans, we develop and test for a two-sided dynamic learning model to assess the degree of learning-by-lending in bank branches and learning-by-repaying for borrowers. The results show that learning-by-lending is negligible, however, learning-by-repaying is small but meaningful, with a shallow learning curve slope of 0.2. The findings have implications for two-sided learning and for policymakers aiming to lower defaults in SBA loans.

Keywords: Two-sided learning; third-party guarantee loans; SBA
JEL Codes: L26; G21; G29

1 Introduction

Small businesses face credit rationing and stricter covenants in receiving loans. To mitigate the potential market failure in small business lending, policymakers around the world have devised third-party loan guarantee programs where the government guarantees a portion of the loan. In the US the Small Business Administration (SBA), as a third-party loan guarantor, guarantees up to 85% of the loan amount. In 2019, the SBA disbursed 47,104 7(a) loans totaling $20.83 billion.[1] The default rates, however, remain high. With one estimate of 1 in 6 loans defaulting between 2006 and 2015 (Voigt & Cambell, 2017), there are increasing calls for reform of the SBA loan programs (Brown & Earle, 2017; Lee, 2018). Related to the benefits of loans, about 3 to 3.5 jobs are created for one million dollars in SBA loans (Brown & Earle, 2017), yet, in a sample of metropolitan areas Lee (2018) found no effect of SBA loans on regional growth. Overall, the SBA loan program has lowered credit constraints for small businesses but its benefits remain mixed.

Moving from the prior works on third-party guarantee loans using a loan as a unit of

[1] Source: https://www.sba.gov/sites/default/files/aboutsbaarticle/WebsiteReport_asof_20190830.pdf

analysis, we consider the role of the endogenous two-sided learning between lenders and borrowers. To our knowledge, there is limited if any effort to develop and test the two-sided learning model in the third-party loan guarantee context. Even for the corporate debt market, the bank learning model was only proposed recently Botsch and Vanasco (2019). With high default rates, the third-party guarantors need to know if banks make loans with lower default over time (learning-by-lending) and whether borrowers learn over time to improve their loan repayment ability (learning-by-repaying).

Related to learning-by-lending, bank branches through relational lending must be able to ‘pick winners’ to ensure the sustainability of third-party guarantee loans. Though this normative goal may be desirable, banks may also engage in moral hazard by transferring risk to the SBA and make sub-par loans to less than desirable loan applicants. For a bank branch, a third-party guarantor loan is a European put option that can be exercised if the borrower defaults (Merton, 1977; Mody & Patro, 1995). Bank branches may, therefore, have adverse incentives to make bad loans and thereby increase inefficient risk-bearing on the third-party guarantor. As such, when it comes to third-party guaranteed loans, banks may not invest adequately in screening and monitoring to improve learning-by-lending.

By developing estimates of two-sided learning or learning-by-lending *and* learning-by-repaying we aim to make the following contributions. First, related to learning-by-repaying, with a significant portion of loan guaranteed by the SBA, the possibility of discharging the loan through bankruptcy, and homestead protections in most US states protecting home equity, borrowers may also engage in moral hazard and may have a limited incentive to lower default over time (Conning, 2005; Vogel & Adams, 1997; Zhu, 2018). On the other hand, however, small business owners are locally embedded, have concerns for reputation in the community, and because a significant portion of their assets is tied in the firm the owners may be more diligent in improving learning-by-repaying.

Second, contributing to the relational lending literature we develop and test a model of two-sided learning Bayesian model (cf. Cisternas, 2018; Sørensen, 2007). Cisternas (2018) focuses on continuous-time learning under imperfect monitoring where learning-driven ratcheting drives signaling motives. Compared to his Markov-based model of pure equilibria strategies from the signal sender, ours is a Bayesian learning model where interactions between both the lender and borrower may influence one another. Sorenson (2007) develops a dynamic learning model based on the multi-armed bandit framework and finds that venture capitalists learn from both past investments (exploitation) and also focus on the option value of future learning (exploration). Our scope includes both the investor (the bank) and the borrower (the small business), but in a relatively lower stake context where exploitation (learning from past loaning and borrowing experiences) is more salient. The proposed model provides an important extension to models on learning over time in the theoretical domain of small business lending.

Third, the proposed model is of significant importance for policymakers. Whether bank branches are proficient at lowering SBA loan default rates or whether repeat borrowers are less likely to default remains an important consideration for policymakers. For example, the SBA nominates some bank branches with demonstrated proficiency in processing and servicing SBA-guaranteed loans as preferred lenders and these designated lenders can directly approve the loans. Controlling for a variety of fixed effects we find that bank branches have a negligible learning-by-lending slope. As such, the findings suggest that training programs or a greater SBA involvement may be necessary to lower default rates and increase selectivity in lending. Supporting the possibility of inefficient risk-bearing by the SBA bank branches may not be willing to invest in lowering their default rates, whereas the borrowers have a greater motivation to somewhat improve their repayment rates over time.

The remainder of the paper is organized as follows. We start by presenting the theoretical background and our estimation model. Thereafter we describe our data and present the results. Finally, we discuss the implications of our findings.

2 Theoretical Development and Hypotheses

The primary mission of third-party loan guarantee programs is to assist small businesses with limited collateral to receive loans at reasonable terms from the banks. Due to limited assets that can be offered as collateral, higher chances of failure, and volatile cash flows, small firms face significant challenges in receiving loans from private banks. Even if small businesses are willing to pay higher interest rates to compensate for their higher riskiness, the resulting higher cost of capital could make a business owner more risk-averse and increase the odds of failure (Everett & Watson, 1998; Herranz et al., 2015). Concerned about lower performance at higher interest rates and the generally higher likelihood of failure of small firms, banks engage in significant credit rationing with small businesses (Conning, 2005; Vogel & Adams, 1997; Zhu, 2018).

To address the potential market failure in small business lending governments around the world have implemented third-party loan guarantee programs. The SBA is the largest private firm lender in the US. Under the SBA's most popular 7(a) loan program, small businesses can receive loans up to $5 million and for up to 25 years. The SBA guarantees up to 85% of loans for amounts up to $150,000 and 75% of loans for amounts greater than $150,000. The 7(a) loans were capped at $2 million until October 2010 and thereafter raised to $5 million. The loans are made to for-profit private businesses and the loan proceeds are used for operations, expansion, and upgrades. The gross approval amount increased from $12.43 billion in 2010 to $23.56 billion in 2019, with default rates continuing to remain high. Though loan defaults are a consideration in the portfolio performance of SBA loans, the SBA also has a non-economic mission to assist small businesses, support jobs, and promote growth. Nevertheless, default rates remain a key concern.

The relational aspect of banking is important for both the banks and businesses in sustaining long-term borrowing and lending relationships. Even with the advent of technology and the availability of credit scores, loans made to borrowers at least 25 miles away from their bank lenders are 10.8 percent more likely to default, and borrowers located at least 50 miles away are 22.1 percent more likely to default on their loans (DeYoung, Frame, et al., 2008; DeYoung, Glennon, et al., 2008). The value of relational lending is further confirmed in Berger et al. (2005), DeYoung et al. (2011), Chakraborty and Hu (2006), and Petersen and Rajan (2002). Small firms focused on transactional technologies in managing relationships with banks are more likely to have their loans denied than those leveraging relationship lending technologies (Angori et al., 2019). Studies continue to find that adverse selection in loans to small firms can be lowered by relational lending and hard financial information collected by technological tools may lead to adverse selection errors (Brighi et al., 2019), with soft information improving access to credit during crisis (Ferri et al., 2019).

2.1 Learning-by-lending

The principal-principal-agent problem in third-party guarantee loans is unique. Related to the principal-principal problem, because a significant portion of the loan is guaranteed, banks may have lower incentives to mitigate moral hazard or improve the monitoring of borrowers. Therefore, SBA may bear a disproportionate amount of risk (Chang et al., 2006; DeYoung, Glennon, et al., 2008; Merton, 1977; Mody & Patro, 1995). Because a guaranteed loan is a European put option, the bank can simply exercise the option with the SBA in case of default. As such, banks can free-ride on such programs and may have a limited incentive to improve their lending outcomes over time.

On the other hand, with most small businesses opting for SBA loans, much of the local economic milieu depends on lending to small firms. Normatively, the learning-by-lending model is salient for bank branches (Botsch & Vanasco, 2019) who must improve screening and monitoring over time (Botsch & Vanasco, 2019; Hughes & Mester, 2008, 2013; Sharpe, 1990), a skill garnered over time by developing a knack for eliciting and collecting soft information from informationally opaque local private firms (Berger & Udell, 1995; Chakraborty & Hu, 2006; M. Petersen & Rajan, 1994; M. A. Petersen & Rajan, 2002). The embedded nature of the banking relationships and the viability of the branch conditional on the economic sustainability of the local region, bank branches may also be motivated to improve learning-by-lending. Theoretically, if bank branches do not improve learning-by-lending over time the local economy could decline due to excess entry and the ensuing business failures. Overall, the long-term implications of not improving learning-by-lending could be detrimental for local branches even if the loans are guaranteed by the third-party guarantor.

2.2 Learning-by-repaying

Due to limited collateral and risky survival prospects, a small business facing credit rationing from banks must have a significant incentive to improve learning-by-repaying. Credit remains a major hurdle to small business growth and survival (Blanchflower et al., 2003). On the one hand, based on signaling theory (Spence, 1978), lower learning-by-repaying sends negative signals to stakeholders. Legitimacy concerns in the task environment (Aldrich, 2008; Aldrich & Pfeffer, 1976) and localized banking relationships (M. Petersen & Rajan, 1994; M. A. Petersen & Rajan, 2002) may increase the incentives of business owners to repay their loans in full. From the task environment perspective, full repayment of loans over time signals reliability and liquidity of business operations to stakeholders. The improved learning-by-repaying is an important consideration given the general reluctance of banks in lending to high-risk small business borrowers (Craig et al., 2007; Haynes, 1996; Riding & Haines Jr, 2001). Signaling to both task environment stakeholders and local banks in the form of repayments is critical for informationally opaque small firms (DeYoung, Glennon, et al., 2008). Even with the advent of credit scores, much of small business exchanges and loans (DeYoung, Glennon, et al., 2008) remain locally embedded and relational. It could also be argued that small businesses may engage in moral hazard by defaulting on loans. With a substantial portion of the loan guaranteed by the SBA, business owners may also engage in excessive risk-taking due to the "house money" effect (Kerr et al., 2015). Because SBA loans could be written off through bankruptcy, the probability of learning-by-repaying is lower.

Overall, although at the individual loan level, it could be argued that business owners may engage in moral hazard due to higher loan guarantee amounts and the option to discharge the loans through bankruptcy, improved learning-by-repayment may send stronger to stakeholders and local bank branches and could be important for owners with concentrated ownership in their firms.

3 The Two-Sided Model of Learning-by-Lending and Learning-by-Repayment

Continuing from the previous discussion on whether bank-branches or borrowers or both improve learning over time, the extant evidence is mixed (Agnese et al., 2018; Cowling & Mitchell, 2003; Kang & Heshmati, 2008), and conditional on country-specific factors (Agnese et al., 2019). According to d'Ignazio and Menon (2013) loan defaults are greater in the short term, but the likelihood is lower in the long term. However, de Blasio et al. (2018) and Saito and Tsuruta (2018) found that, in general, firms receiving third-party guarantee loans are more likely to default. Uesugi et al. (2010) found no differences in default rates between Japanese firms receiving third-party guarantee loans or traditional loans, however, Ono et al. (2014) found that those receiving government-sponsored loans realized greater performance decline. In France, those receiving such loans had a higher chance of bankruptcy (Lelarge et al., 2010), in the UK Agnese et al. (2018) finds no effect on bankruptcies, in Portugal Farinha and Félix (2015) found that an increase in the loan volume increased bankruptcies, and in the Korean context Kang and Heshmati (2008) found mixed effects, however, Oh et al. (2009) found a positive relationship between credit guarantee loans and firm performance.

Our proposed framework is rooted in the theoretical basis of relational banking with the unit of analysis at the bank-branch-business-level. The proposed dual-sided learning framework was discussed in the qualitative study by Uzzi and Lancaster (2003) who highlight the role of knowledge transfer and learning through relational ties. Rooted in the social embeddedness framework the commercial ties are rooted in social transactions and greater embeddedness facilitates relationships that allow for learning. Learning-by-lending and learning-by-repayment are less rooted in arms-length type information (e.g., the credit score of a business), but the complex network of ongoing relationships between banks and borrowers. The idiosyncratic information of borrowers relates to firm strategy, resources, and competitive challenges along with a richer understanding of stakeholder relationships. The learning process is two-sided as the bank learns and borrowers create business signals for banks and exchange partners. The proposed two-sided learning framework aims to assess learning for both banks and borrowers. We propose hypotheses jointly because our empirical model aims to test the two-sided learning by jointly considering learning by both lenders and borrowers.

Hypothesis 1: *Learning-by-lending (lower third-party guarantee loan defaults over time) improves for a bank branch over time.*

Hypothesis 2: *Learning-by-repayment (lower third-party guarantee loan defaults* *over time) improves for a small business borrower over time*.

3.1 Analytical model

Next, we present the analytical model associated with the above theoretical discussion on dual-sided learning. An entrepreneur has an underlying, unobserved ability to repay a loan at period t, which we denote by y_t^*. If $y_t^* > 0$ she pays the installment successfully in which case we observe an indicator $d_t = 1$, otherwise we have $y_t^* \leq 0$ and we observe $d_t = 0$. The usual probit model is

$$y_t^* = x'_t\beta - u_t, u_t \sim \mathcal{N}(0,1), t = 1, \dots, T, \tag{1}$$

where x_t is a $k \times 1$ vector of covariates with associated coefficients β (also a $k \times 1$ vector). The probability of successful payment is

$$\Pr(d_t = 1|x_t, \beta) = \Pr(y_t^* > 0|x_t, \beta) = \Phi(x'_t\beta), \tag{2}$$

where $\Phi(\cdot)$ is the standard normal distribution function. A certain advance is to use a dynamic probit model:

$$y_t^* = \rho y_{t-1}^* + x'_t\beta - u_t, u_t \sim \mathcal{N}(0,1), t = 1, \dots, T, \tag{3}$$

to account for persistence in the successful payment ability (provided $\rho > 0$). Estimation of the static probit model is easy and it is available in most software packages but the estimation of the dynamic probit is less straightforward and is, usually, carried out using Bayesian methods organized around Markov Chain Monte Carlo (MCMC), see Campolieti (2001), and Soyer and Sung (2013) *inter alia*.

Related to a dynamic model the entrepreneur has applied in the past for loans, some of which were successfully granted to her while others did not. On the granted loans, she defaulted on some but repaid successfully for others. Did she learn anything from this behavior? This is the first important question. But if she did learn, so did the financial institutions that granted her the loan.

In the time interval $\{1, \dots, T\}$ she has applied for a loan at periods $\tau_1, \dots, \tau_M$ the respective amounts being $B_{\tau_1}, \dots, B_{\tau_M}$. Some of these loans were granted while others were not. Her repayment ability is influenced by this history but so did the decisions of financial institutions.

Suppose we are at a time τ_m ($m \in \{1, \dots, M\}$) and the entrepreneur applies for a loan. Her repayment ability is $y^*_{\tau_m}$. The financial institution has a profit to be made from this loan, say $\pi^*_{\tau_m}$ which is unobserved but depends on institutional as well as entrepreneurial characteristics, most notably $\{y^*_\tau, \tau \leq \tau_m\}$. We have an indicator $D_t = 1$ if $\pi^*_{\tau_m} > 0$ and zero otherwise. A general form for π^*_t is

$$\pi^*_t = z'_t\gamma - \varepsilon_t, \varepsilon_t \sim \mathcal{N}(0,1), \tag{4}$$

where z_t is a $K \times 1$ vector of covariates with associated coefficients γ (also a $k \times 1$ vector). This profit formulation is deficient in the sense that the history of the applicant is not taken into account. The financial institution knows her history so this information has to be somewhere among the z_ts. More realistically, we assume:

$$\pi^*_t = z'_t\gamma + \sum_{\tau \leq t} \delta_\tau B_\tau D_\tau d_\tau - \varepsilon_t, \varepsilon_t \sim \mathcal{N}(0,1). \tag{5}$$

The summations $\sum_{\tau \leq t}$ stand for aggregating history, δ_τ are coefficients and, as we remarked before, B_τ is the requested loan at period τ, $D_\tau = 1$ if the loan was granted, and $d_\tau = 1$ if our entrepreneur successfully repaid. So, at some period $\tau < t$, say, the effect of the profit of the institution is $\delta_\tau B_\tau$ provided the loan was granted (i.e. $D_\tau = 1$) and zero otherwise. This, however, ignores what the entrepreneur did with past loans. At period $\tau = t$ it is uncertain whether the institution will grant the loan or not and whether the entrepreneur will repay or not. But history is known. So, we have

$$\sum_{\tau \leq t} \delta_\tau B_\tau D_\tau d_\tau = \delta_t B_t D_t d_t + \sum_{\tau < t} \delta_\tau B_\tau D_\tau d_\tau. \tag{6}$$

Therefore, we may write the profit of the institution as:

$$\pi_t^* = \lambda\pi_{t-1}^* + \alpha\tilde{y}_t^* + z'_t\gamma - \varepsilon_t, \varepsilon_t \sim \mathcal{N}(0,1), \tag{7}$$

where the α coefficient introduces persistence on how the institution views profit capability for our entrepreneur. Here, $\tilde{y}_t^*$ is the institution's estimate of the entrepreneur's ability to repay:

$$\tilde{y}_t^* = \varrho\tilde{y}_{t-1}^* + x'_t\varphi + \sum_{\tau<t} \delta_\tau B_\tau D_\tau d_\tau - \xi_t, \xi_t \sim \mathcal{N}(0,1). \tag{8}$$

This estimate is persistent (provided $\varrho > 0$) and depends on the history of our entrepreneur. Essentially, it is a forecast of her ability to repay successfully loans of different amounts. In this equation, we include the entrepreneur's characteristics x_t with coefficients φ (a $k \times 1$ vector).

So, we have equations (3) and (7) along with the indicators

$$d_t = \begin{cases} 1, & \text{if } y_t^* > 0, \\ 0, & \text{otherwise,} \end{cases} \text{and} D_t = \begin{cases} 1, & \text{if } \pi_t^* > 0, \\ 0, & \text{otherwise.} \end{cases} \tag{9}$$

Suppose, in the interest of simplicity that we turn off all dynamics ($\rho = \lambda = \varrho = 0$). Then, we have the following cases and their respective probabilities, *conditional* on $\tilde{y}_t^*$.

	$d_t = 0$	$d_t = 1$
$D_t = 0$	A_t	B_t
$D_t = 1$	Γ_t	Δ_t

Here the probabilities are:

$$A_t = [1 - \Phi(x'_t\beta)][1 - \Phi(z'_t\gamma + \alpha\tilde{y}_t^*)] = \Phi(-x'_t\beta)\Phi(-z'_t\gamma - \alpha\tilde{y}_t^*), \tag{10}$$

$$B_t = \Phi(x'_t\beta)\Phi(-z'_t\gamma - \alpha\tilde{y}_t^*), \tag{11}$$

$$\Gamma_t = \Phi(-x'_t\beta)\Phi(z'_t\gamma + \alpha\tilde{y}_t^*), \tag{12}$$

$$\Delta_t = \Phi(x'_t\beta)\Phi(z'_t\gamma + \alpha\tilde{y}_t^*). \tag{13}$$

Under the assumption of independence between $u_t, \varepsilon_t, \xi_t$ the likelihood function is

$$L(\theta) = \left\{\prod_{t=1}^{T} A_t^{\mathbb{I}(d_t=1,D_t=1)}\, B_t^{\mathbb{I}(d_t=1,D_t=0)}\Gamma_t^{\mathbb{I}(d_t=0,D_t=1)}\Delta_t^{\mathbb{I}(d_t=D_t=1)}\right\}\cdot \exp\left\{-\frac{1}{2}\sum_{t=1}^{T}\left(\tilde{y}_t^* - \delta\sum_{\tau<t} B_\tau\, D_\tau d_\tau\right)^2\right\}, \tag{14}$$

where $\mathbb{I}(d_t = i, D_t = j) = 1$ if the condition in the parentheses holds true, and zero otherwise ($i, j \in \{0,1\}$), and θ denotes the entire vector of unknown parameters. We have also made the assumption $\delta_\tau = \delta$ (for all τ). The second term comes from (8).

We also want to include a condition that the bank's forecast does *not* overstate the entrepreneur's ability to pay:

$$\tilde{y}_t^* \leq y_t^*. \tag{15}$$

This introduces the constraint:

$$\begin{gathered} x'_t\varphi + \sum_{\tau<t} \delta_\tau\, B_\tau D_\tau d_\tau - \xi_t \leq x'_t\beta - u_t \Rightarrow \\ u_t - \xi_t \leq x_t'(\beta - \varphi) - \delta\sum_{\tau<t} B_\tau\, D_\tau d_\tau. \end{gathered} \tag{16}$$

The probability of this event is:

$$\begin{aligned} \Pr\left(u_t - \xi_t \leq x_t'(\beta - \varphi) - \delta\sum_{\tau<t} B_\tau\, D_\tau d_\tau\right) \\ = \Phi\left(\frac{x_t'(\beta - \varphi) - \delta\sum_{\tau<t} B_\tau\, D_\tau d_\tau}{2}\right). \end{aligned} \tag{17}$$

The bank wishes to make this probability large enough, say greater than $\bar{\pi}$ (perhaps 0.95), in which case we have the constraint:

$$x_t{}'(\beta - \varphi) - \delta \sum_{\tau<t} B_\tau D_\tau d_\tau \geq \bar{\kappa} \equiv 2\Phi^{-1}(\bar{\pi}) = 3.96, \tag{18}$$

if $\bar{\pi} = 0.95$, and $\Phi^{-1}(\cdot)$ denotes the inverse standard normal distribution function.[2] In turn, we have to maximize the likelihood function in (14) subject to (18). This can be done only numerically.

To simplify the computation of the maximum likelihood estimator (MLE) we can replace (18) with the following stochastic version:

$$x_t{}'(\beta - \varphi) - \delta \sum_{\tau<t} B_\tau D_\tau d_\tau = \bar{\kappa} + \zeta_t + U_t, \tag{19}$$

where $\zeta_t \sim^{iid} \mathcal{N}\,(0, \sigma_\zeta^2)$ represents the *bank's deviations from optimal policy* and U_t is a non-negative random variable, for example $U_t \sim^{iid} \mathcal{N}_+\,(0, \sigma_U^2)$. *The greater U_t is the greater is conservativeness in bank's forecasts of an entrepreneur's ability to repay*.

Since this is a stochastic frontier model (Kumbhakar and Lovell, 2000, pp. 78 and 82) the density function of the composed error $e_t = \zeta_t + U_t$ is $f_e(e_t) = \frac{2}{\sigma}\phi\left(\frac{e_t}{\sigma}\right)\Phi\left(\frac{\Lambda e_t}{\sigma}\right)$, where $\sigma^2 = \sigma_\zeta^2 + \sigma_U^2$, $\Lambda = \frac{\sigma_U}{\sigma_\zeta}$, and $\phi(\cdot)$ is the standard normal density function. With this modification, the likelihood function for the static model becomes:

$$L(\theta) \propto \left\{\prod_{t=1}^{T} A_t^{\mathbb{I}(d_t=1,D_t=1)} B_t^{\mathbb{I}(d_t=1,D_t=0)} \Gamma_t^{\mathbb{I}(d_t=0,D_t=1)} \Delta_t^{\mathbb{I}(d_t=D_t=1)}\right\} \cdot$$
$$\exp\left\{-\frac{1}{2}\sum_{t=1}^{T}\left(\tilde{y}_t^* - \delta \sum_{\tau<t} B_\tau D_\tau d_\tau\right)^2\right\} \cdot \tag{20}$$
$$\sigma^{-T}\prod_{t=1}^{T}\phi\left(\frac{x_t{}'(\beta - \varphi) - \delta\sum_{\tau<t} B_\tau D_\tau d_\tau - \bar{\kappa}}{\sigma}\right)\Phi\left(\Lambda\frac{x_t{}'(\beta - \varphi) - \delta\sum_{\tau<t} B_\tau D_\tau d_\tau \text{ -}}{\sigma}\right.$$

The ratio Λ measures whether the bank's optimization error is "small", and the amount of U_t (inefficiency) can be used to determine by how much the constraint is exceeded provided

[2]The number $\bar{\kappa}$ would be 4.65 if $\bar{\pi}$ was 0.99.

we set $\bar{\kappa} = 0$. This is quite useful as in practice we do not know $\bar{\kappa}$ and we would like to estimate it. Its time-varying estimate is the conditional expectation

$$\hat{U}_t = \mathbb{E}(U_t|\text{data}) = \sigma_* \left[\frac{\phi(\Lambda e_t/\sigma)}{\Phi(\Lambda e_t/\sigma)} + \Lambda e_t/\sigma\right], \tag{21}$$

where $\sigma_* = \sqrt{\sigma_\zeta^2 + \sigma_U^2}$, and $e_t = x_t'(\beta - \varphi) - \delta \sum_{\tau<t} B_\tau D_\tau d_\tau$. We believe, however, that these slacks could be autoregressive:

$$\ln U_t = \alpha_U + \rho_U \ln U_{t-1} + \epsilon_t, \epsilon_t \sim iid\ \mathcal{N}_+(0, \sigma_U^2). \tag{22}$$

As we use Bayesian techniques organized around MCMC, it is not necessary to rely on estimates such as (21). Instead, for each MCMC draw indexed by $s \in \{1, \dots, S\}$, we have draws $U_t^{(s)}$. The posterior mean estimate of slacks can be computed accurately as

$$\hat{U}_t = S^{-1} \sum_{s=1}^{S} U_t^{(s)} \tag{23}$$

The estimates (posterior means) of ρ, λ, ϱ with learning estimates of learning-by-repaying and learning-by-lending$1 - \rho$ and $1 - \varrho$, respectively.

Based on the theoretical discussion and the proposed derived in equations (1)-(23), we propose:

4 Data and Methods

To test for the proposed hypotheses, we draw on the data of all Small Business Administration 7(a) loans from fiscal years 1999 to September 2019[3]. The data is publicly available, and it was retrieved on September 17, 2019, from SBA.gov website.[4] The initial sample includes 1,559,762 SBA 7(a) loans. To be included in the sample, we required that a borrower must have taken at least two loans and the bank branch must have made at least 50

[3] Because the disbursement of the loan occurs after the date of approval, we use the reported fiscal year for a loan as the year of the loan in conducting our analysis.
[4] Source: https://www.sba.gov/about-sba/open-government/foia#section-header-32

loans. We also conduct the same analysis for borrowers with a minimum of three loans. Based on these filters, our final sample included 1,020,039 loans (76,574 borrowers-1,105 bank branches [for borrowers with two loans] and 10,452 borrowers-548 bank branches [for borrowers with >= 3 loans]). The unique bank branch identifier is based on the combination of the bank name, street, city, state, and zip code. The unique borrower identifier is based on the borrower's name, street, city, state, and zip code.

4.1 Measures

The outcome variable is whether a loan is defaulted by the borrower. If the loan was paid in full or continued beyond 2019 it was coded as censored, and if the loan defaulted it was coded as 1. We dropped loans exempt from public disclosures or loans that were canceled.

The control variables are the gross approval amount, the gross charge-off amount (= 0 if the loan is paid in full), and months to chargeoff. We control for the gross approval amount as larger loans are subject to greater due diligence and monitoring by lenders, and therefore, less likely to default. Loans active for longer periods, or longer charge-off periods, are less likely to default. Small businesses facing volatile revenue streams and lower profitability may be better able to pay off loans over longer chargeoff periods than over shorter chargeoff periods.

We control for the loan delivery method,[5] interest rate of the loan, business type (Individual, Partnership, or Corporation), whether the loan is a revolver loan (=revolving line of credit, else = 0 for term loan), and the self-reported jobs supported on the loan application.

[5] CA = Community Advantage; CLP = Certified Lenders Program; COMM EXPRS = Community Express (inactive);DFP = Dealer Floor Plan (inactive); DIRECT = Direct Loan (inactive); EWCP = Export Working Capital Program; EXP CO GTY = Co-guaranty with Export-Import Bank (inactive); EXPRES EXP = Export Express; GO LOANS = Gulf Opportunity Loan (inactive); INTER TRDE = International Trade; OTH 7A = Other 7(a) Loan; PATRIOT EX = Patriot Express (inactive); PLP = Preferred Lender Program; RLA = Rural Lender Advantage (inactive); SBA EXPRES = SBA Express; SLA = Small Loan Advantage; USCAIP = US Community Adjustment and Investment Program; and Y2K = Y2K Loan (inactive)

SBA has a variety of loan programs with different goals and objectives, with several loan programs focused on natural disasters or targeted business programs. To control for these variations in goals and objectives across loan programs we controlled for the loan delivery method. Higher interest rates may increase the odds of default. Because individual and partnership modes of the organization carry significant liability, relative to firms organized as a corporation, we expect that sole proprietors and partnerships may be more judicious in borrowing and repaying the loans. The loans for revolving lines of credit are a part of the regular operations of a business and are therefore more likely to be repaid. Finally, the self-reports of the expected number of jobs supported from the loan may not be a reliable indicator of value creation but may influence the loan application process.

Table 1 presents the sample descriptives.

--------------Insert Tables 1-3 about here---------------

4.2 Model Specification

To summarize we have the following model to estimate:

$$\text{Entrepreneur Ability to Repay:} \, y_t^* = \rho y_{t-1}^* + x'_t\beta - u_t, u_t \sim \mathcal{N}(0,1), t = 1, \dots, T. \tag{24}$$

$$\text{Bank Latent Profit:} \, \pi_t^* = \lambda\pi_{t-1}^* + \alpha\tilde{y}_t^* + z'_t\gamma - \varepsilon_t, \varepsilon_t \sim \mathcal{N}(0,1). \tag{25}$$

$$\text{Bank Forecast of Ability to Repay Constraint:} \, x_t'(\beta - \varphi) - \delta\sum_{\tau<t} B_\tau D_\tau d_\tau = \bar{\kappa} + \zeta_t + U_t, \tag{26}$$

($\zeta_t \sim^{iid} \mathcal{N}\,(0, \sigma_\zeta^2)$ represents the bank's deviations from optimal policy and U_t variable, for example $U_t \sim^{iid} \mathcal{N}_+\,(0, \sigma_U^2)$ represents the bank's conservativeness in the estimated forecast of an entrepreneur's ability to repay). For the interpretation of the effects of hypotheses, the parameters of interest are ρ (learning-by-repaying) and δ (learning-by-lending). Notice that (24) corresponds to (7), (25) corresponds to (4), and (26)) corresponds to (18).

We implement MCMC as described in the Technical Appendix using 150,000 iterations the first 50,000 of which are discarded to mitigate possible start-up effects. Our priors for regression parameters are flat across the real line, and the same is true for the logarithms of scale parameters σ_ζ and σ_U. In Figure 1 we report sample distributions of $\widehat{U}_t$ in (23) which is estimated for each MCMC draw as in (21). On average, these estimates are 0.148 and 0.283 for the static and dynamic models, respectively (the sample standard deviations are, respectively, 0.023 and 0.038). To understand the implications, notice that the posterior moments of $\bar{\kappa}$ from Table 1 are 0.891 and 4.71 for the static and dynamic models, respectively (the posterior standard deviations are, respectively, 0.442 and 0.032). Therefore, $\bar{\kappa}$ could be zero in the static model but not in the dynamic model. Our posterior mean estimate (4.71) is remarkably between 3.96 and 4.65 at probabilities $\bar{\pi}$=0.95 and 0.99 associated with (17). Besides that, in the dynamic model, banks appear to be overly conservative as the constraint in (26) allows for a slack close to 28.3% and ranges from, roughly, 17% to 45%. According to the static model (straight line in Figure 1), the static model underestimated this slack as it averages 14.8% and ranges, roughly, from slightly over 5% to 23%. So the upper bound of the slack from the static model is close to the posterior mean for the dynamic model.

In tables 2 and 3, the ρ (learning-by-repaying) parameter is 0.814 (s.e. = 0.022) and 0.799 (s.e. = 0.015), respectively. The estimates close to 0.8 translate to a learning curve slope of 0.2 (1 minus 0.8). Though the effect size is small, it is meaningful. In Tables 2 and 3, the δ (learning-by-lending) parameter is 0.976 (s.e. = 0.005) and 0.915 (s.e. = 0.003), respectively. Subtracting these parameters from 1 yields a very small slope for learning. We, therefore, do not infer support for Hypothesis 2. Overall, learning-by-repaying seems feasible and the lack of support for limited, if any, learning-by-lending is telling.

We note that the estimates for the static and the dynamic model are different in effect sizes. The estimates based on the dynamic model are based on persistence or path dependence, thus, lowering the overall effect size. The estimates for the static models are larger, indicating that neglecting dynamic estimates could lead to inflated estimates. Indicating the dynamic models provide improved estimates, the pseudo-R-squared is much higher under the dynamic specification.

5 Discussion and Conclusion

Ours is the first study focusing on the two-sided learning between banks and borrowers in the third-party loan guarantee programs. The results provide very limited evidence on two-sided learning in third-party loan guarantee programs. Related to learning-by-lending our results are consistent with the moral hazard arguments in financial economics, that banks disproportionately transfer risk to loan guarantors. The negligible learning rate for banks is indicative of lower concerns for improving long-term capacity in improving third-party loan outcomes. In interpreting these outcomes we caution that this lack of learning does not apply to non-third-party guarantee loans. Consistent with the broader arguments on such guaranteed loans as a European put option, bank branches do not seem to invest in improving loan outcomes for SBA loans and therefore SBA must be bearing disproportionate risk.

Of interest and consistent with business concerns of borrowers, the learning-by-repayment does seem to have a small but more meaningful rate. Though the slope of the learning curve is about 0.2, it is a meaningful effect size given the idiosyncratic business and personal conditions a business owner faces in repaying the loan. Loans are borrowed under distinct firm and personal needs and the ensuing repayments are also subject to distinct industry and environmental forces. As such, a small effect size is meaningful and is indicative of the borrowers improving their repayment capability over time. SBA also provides training programs and consulting services for business owners. A substantial amount of resources in improving awareness and management of finances are expended. Our results, though not being able to parse out the effect of training and consulting from the borrower's unobservable skills, we find that there is a shallow learning slope (0.2) for the borrowers. In other words, repeat borrowers of SBA loans may be of lower risk to the SBA than the bank branches with negligible improvements in learning-by-lending. Two data limitations—firm and branch-specific unobservables over time and local conditions that promote relational banking more than in other areas—limit our ability to draw causal inferences from the available data sources. Nevertheless, the two-sided Bayesian learning model allows for controls for the branch-borrower-loan fixed effects over time.

Lack of support for learning-by-lending, therefore, indirectly supports the long-held inefficient risk-bearing hypothesis in the third-party loan guarantee literature (Brickley & Dark, 1987; Stiglitz, 1993). The findings provide the basis for future exploration of the principal-principal agency problem in the literature. The inefficient risk bearing is an important consideration not only for academic research but also for policymakers based on limited incentives among bank branches to improve learning-by-lending in third-party guarantee loans. Increasing inefficient risk-bearing by the SBA calls for a closer assessment of the potential adverse selection in selecting loan recipients and the moral hazard during the loan duration.

5.1 Practical Implications

Related to the practical implications of our findings, the implications are significant for the SBA, banks, and small business owners. For the banks a closer examination of limited learning-by-lending for SBA loans is necessary. The negligible learning rate is indicative of the lack of sustained improvements in the screening and monitoring of loans. The loan guarantee seems to provide perverse incentives in lowering the odds of default. Perhaps due to the non-economic goals of SBA stricter lending norms or audits may not be enforced, however, the negligible learning rate also begs the question of whether SBA can create a centralized mechanism to fund SBA loans. With improved technology and the limited ability of the banks to improve their lending outcomes, and the seemingly limited indirect evidence of relational banking (else both sides would improve learning over time) it might be advisable to consider removing banks as intermediaries or increasing monitoring of banks. Though this is among the first study, the data is comprehensive and representative and the negligible learning-by-lending calls on SBA administrators to delve into this issue further.

For banks, the results show that investments in improving learning-by-lending may advisable to sustain their presence and embeddedness in the local community, especially with increased bank competition in recent decades. Reducing the brick-and-mortar footprint of banks, increasing the prevalence of online lending platforms such as LendingClub.com, and increasing bank deregulation calls on banks to leverage relational assets even to a greater extent. The SBA loans are central to the economic vitality of the local economy as most small firms rely on SBA loans. Improving the sustainability of this program is in the long-term interest of the banks.

For small business owners, the improving ability to repay SBA loans over time is an important consideration in signaling legitimacy and sustaining relationships. Learning-by-repaying could mitigate concerns for higher opacity and particularism in small firms. For SBA in terms of assessing “bang for the buck” in investing in training programs, improving training and guidance in improving repayment rates could be beneficial.

5.2 Limitations and Directions for Future Research

The study is not without limitations. First, though we control for a variety of confounding factors, the available data is coarse-grained. Though the SBA loan data is widely used we lack the data on the micro-dynamics of the loan origination and monitoring process. Though some recent studies have matched loan recipients (Brown & Earle, 2017) with the confidential firm census data or others relying on sales tax data in Texas, similar to several learning studies we lack the data on microdynamics to provide the level of richness available in experimental studies. Future studies could focus on microdynamics in a lab setting or draw on qualitative data. Second, although the data is representative of a major third-party loan guarantee program in the US, the findings are not generalizable to other loan guarantee programs across the world.

Overall, this study contributes to our understanding of a two-sided model of learning-by-lending and learning-by-repayment. Supportive of disproportionate risk transfer by banks to the SBA, we find support for negligible learning-by-lending for SBA loans. Indicative of borrower willingness to generate signals in a credit rationed lending market, small business borrowers exhibit a small but meaningful learning rate. We hope that the findings prime future research on learning between SBA, bank branches, and borrowers to further lower default rates and improve loan allocations for this economic program central to the economic vitality of the US.

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TABLE 1 Sample Descriptives.

	Borrower == 2 loans					Borrower >= 3 loans				
Variable	Obs	Mean	s.d.	Min	Max	Obs	Mean	s.d.	Min	Max
Loan default	76,574	0.1609	0.3674	0	1	10,452	0.0999	0.2999	0	1
Gross approval amount	76,574	172,961.70	320,878.10	200	5,000,000	10,452	212,660.50	385,932.80	300	5,000,000
SBA guarantee percentage	76,574	123,473.80	250,150.90	100	4,500,000	10,452	159,191.60	315,007.90	150	4,500,000
Jobs supported	76,574	9	25	0	4479	10,452	13	112	0	4546
Months to charge off	76,572	88	61	0	385	10,452	70	58	0	317
Gross charge off amount	76,574	14,492.28	71,261.30	0	2,537,617	10,452	8,763.43	58,436.77	0	2,272,099
Initial interest rate	21,263	6.01	1.27	1	11.5	3,746	5.73	1.16	0.66	11.75
Revolver status	26,032	1	0	1	1	2,406	1	0	1	1
Counts of loans across categories										
Corporation	61,340					8,962				
Individual	13,126					1,224				
Partnership	2,103					266				
CA = Community Advantage	8					-				
CLP = Certified Lenders Program	2,656					369				
COMM EXPRS = Community Express (inactive)	1,639					140				
DFP = Dealer Floor Plan (inactive)	17					4				
EWCP = Export Working Capital Program	651					457				
EXP CO GTY = Co-guaranty with Export-Import Bank (inactive)	7					11				
EXPRES EXP = Export Express	251					54				
GO LOANS = Gulf Opportunity Loan (inactive)	329					76				
INTER TRDE = International Trade	261					54				
OTH 7A = Other 7(a) Loan	9,823					2,469				
PATRIOT EX = Patriot Express (inactive)	841					121				
PLP = Preferred Lender Program	14,087					1,920				
RLA = Rural Lender Advantage (inactive)	53					5				
SBA Express	45,139					4,591				
SLA = Small Loan Advantage	800					176				
USCAIP = US Community Adjustment and Investment Program	9					1				
Y2K = Y2K Loan (inactive)	3					2				

TABLE 2 Empirical results ($\geq \mathbf{2}$ loans)

	Static model	Dynamic model
Structural Parameters		
ρ	–	0.814
		(0.022)
λ	–	0.922
		(0.006)
ϱ	–	0.976
		(0.005)
α	0.0061	0.096
	(0.0013)	(0.0020)
δ	–0.0011	0.0071
	(0.0044)	(0.007)
$\bar{\kappa}$	0.891	4.710
	(0.442)	(0.032)
σ_ζ	1.315	0.534
	(0.051)	(0.014)
σ_U	0.720	0.813
	(0.044)	(0.022)
α_U	–0.003	–0.0044
	(0.002)	(0.0019)
ρ_U	0.0031	0.515
	(0.022)	(0.0033)
$\widehat{U}_t$	0.139	0.274
	(0.029)	(0.037)
Explanatory Variables (x_t) in equation (24)		
percent SBA guarantee	0.041	0.034
	(0.017)	(0.006)
Gross Approval	–0.029	–0.023
	(0.009)	(0.003)
Gross Charge Off Amount	0.004	0.007
	(0.001)	(0.001)
Months to charge off	0.013	0.022
	(0.002)	(0.002)
Initial Interest Rate	0.001	–0.0032
	(0.001)	(0.001)
Business Type=Individual	reference category	reference category
Partnership	0.0045	–0.0053
	(0.0012)	(0.0014)
Corporation	–0.0017	0.0033
	(0.0023)	(0.0005)
Revolver Status	–0.002	0.0055
	(0.0045)	(0.0011)
Jobs Supported	–0.020	–0.013
	(0.0015)	(0.0024)
Explanatory Variables (z_t) in (25)		
percent SBA guarantee	0.0017	0.0240
	(0.0022)	(0.0085)
Gross Approval	–0.002	0.0044
	(0.004)	(0.0012)

Gross Charge Off Amount	0.044 (0.0012)	–0.033 (0.005)
Months to charge off	0.0045 (0.0001)	–0.0051 (0.0012)
Initial Interest Rate	–0.0033 (0.0002)	0.0017 (0.0003)
Business Type=Individual	reference category	reference category
Partnership	–0.0014 (0.0020)	–0.0040 (0.0013)
Corporation	–0.0022 (0.0015)	0.0017 (0.0004)
Revolver Status	0.0030 (0.0071)	-0.0041 (0.0006)
Jobs Supported	–0.0013 (0.0022)	-0.0022 (0.0002)
Explanatory Variables (x_t) in equation (8)		
percent SBA guarantee	0.0014 (0.0021)	0.0032 (0.0004)
Gross Approval	–0.017 (0.0032)	0.0047 (0.0004)
Gross Charge Off Amount	0.0044 (0.0012)	–0.0082 (0.0004)
Months to charge off	0.0016 (0.0019)	0.0082 (0.0015)
Initial Interest Rate	0.0033 (0.0012)	0.0981 (0.017)
Business Type=0	reference category	reference category
Business Type=1	0.0017 (0.0001)	0.0034 (0.0010)
Business Type=2	0.0018 (0.0001)	–0.0039 (0.003)
Revolver Status	–0.0044 (0.0003)	0.022 (0.003)
Jobs Supported	-0.0022 (0.0003)	0.0016 (0.0021)
pseudo R^2	0.244 $^{(a)}$ 0.104 $^{(b)}$	0.589 $^{(a)}$ 0.617 $^{(b)}$

Notes: Reported are parameter estimates (posterior means) with posterior standard deviations in parentheses. Pseudo-R^2 is computed as the posterior mean of correctly predicted cases in (a) the ability to repay equation and (b) the bank latent profit equation. “Reference category” means that the corresponding dummy variable is omitted so the coefficients (posterior means) variables are deviations relative to the reference category. In both models, we include dummy variables for Bank Name, Bank Zip, Bank State, Bank City, SBA District Office, Congressional District. The loan type dummies are included in the regression but not reported for brevity.

TABLE 3 Empirical results (≥ 3 loans)

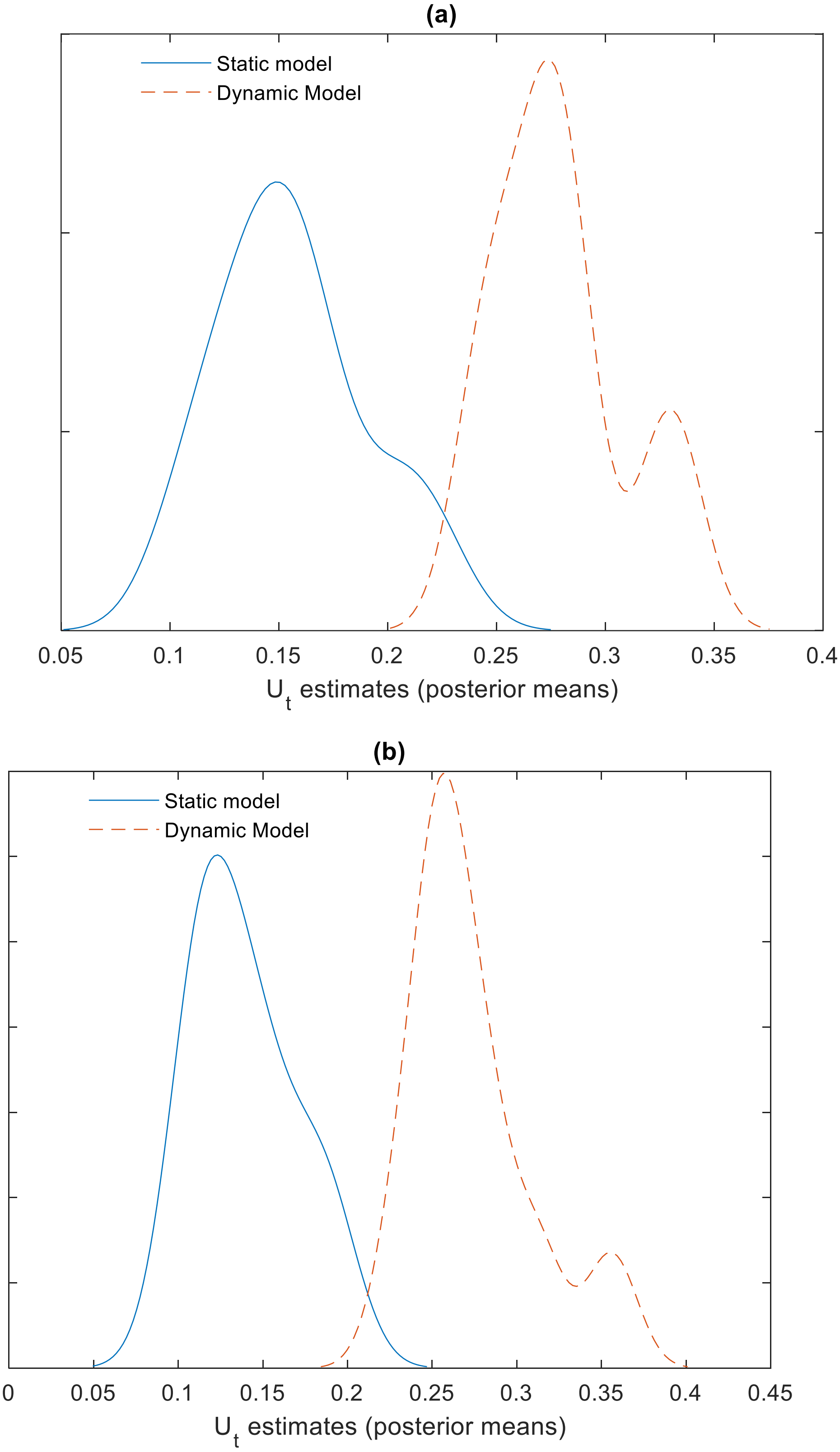
Structural Parameters		Static model	Dynamic model
	ρ	–	0.799 (0.015)
	λ	–	0.877 (0.005)
	ϱ	–	0.915 (0.003)
	α	0.0059 (0.0012)	0.090 (0.0017)
	δ	–0.0010 (0.0024)	0.0065 (0.005)
	$\bar{\kappa}$	0.844 (0.133)	4.619 (0.022)
	σ_ζ	1.445 (0.036)	0.634 (0.012)
	σ_U	0.822 (0.041)	0.717 (0.020)
	α_U	–0.004 (0.001)	–0.0055 (0.0011)
	ρ_U	0.0022 (0.017)	0.544 (0.0030)
	$\widehat{U}_t$	0.156 (0.035)	0.279 (0.030)
Explanatory Variables (x_t) in equation (24)			
percent SBA guarantee		0.035 (0.012)	0.037 (0.007)
Gross Approval		–0.021 (0.008)	–0.020 (0.004)
Gross Charge Off Amount		0.005 (0.001)	0.005 (0.002)
Months to charge off		0.017 (0.001)	0.021 (0.002)
Initial Interest Rate		0.003 (0.001)	–0.0041 (0.002)
Business Type=Individual		reference category	reference category

Partnership	0.0041	–0.0052
	(0.0013)	(0.0012)
Corporation	–0.0013	0.0028
	(0.0021)	(0.0003)
Revolver Status	–0.001	0.0052
	(0.001)	(0.0013)
Jobs Supported	–0.017	–0.015
	(0.0022)	(0.0021)
Explanatory Variables (z_t) in equation (25)		
percent SBA guarantee	0.0013	0.0255
	(0.0013)	(0.0077)
Gross Approval	–0.003	0.0035
	(0.001)	(0.0014)
Gross Charge Off Amount	0.041	–0.038
	(0.0013)	(0.004)
Months to charge off	0.0039	–0.0048
	(0.0002)	(0.0031)
Initial Interest Rate	–0.0034	0.0019
	(0.0004)	(0.0005)
Business Type=Individual	reference category	reference category
Partnership	–0.0013	–0.0038
	(0.0021)	(0.0018)
Corporation	–0.0017	0.0019
	(0.0011)	(0.0007)
Revolver Status	0.0022	-0.0034
	(0.0067)	(0.0003)
Jobs Supported	–0.0018	-0.0020
	(0.0021)	(0.0002)
Explanatory Variables (x_t) in (8)		
percent SBA guarantee	0.0017	0.0034
	(0.0023)	(0.0006)
Gross Approval	–0.013	0.0043
	(0.0035)	(0.0004)
Gross Charge Off Amount	0.0037	–0.0076
	(0.0013)	(0.0002)
Months to charge off	0.0013	0.0077
	(0.0021)	(0.0033)
Initial Interest Rate	0.0027	0.0885
	(0.0014)	(0.014)
Business Type=Individual	reference category	reference category
Partnership	0.0014	0.0030

	(0.0002)	(0.0013)
Corporation	0.0016	–0.0031
	(0.0002)	(0.002)
Revolver Status	–0.0041	0.025
	(0.0005)	(0.004)
Jobs Supported	-0.0026	0.0014
	(0.0004)	(0.0020)
pseudo R^2	0.248 $^{(a)}$	0.599 $^{(a)}$
	0.112 $^{(b)}$	0.613 $^{(b)}$

Notes: Reported are parameter estimates (posterior means) with posterior standard deviations in parentheses. Pseudo-R^2 is computed as the posterior mean of correctly predicted cases in (a) the ability to repay equation and (b) the bank latent profit equation. “Benchmark” means that the corresponding dummy variable is omitted so the coefficients (posterior means) variables are deviations relative to the benchmark category. In both models, we include dummy variables for Bank Name, Bank Zip, Bank State, Bank City, SBA District Office, Congressional District. The loan type dummies are included in the regression but not reported for brevity.

FIGURE 1. Sample distributions of $\widehat{\boldsymbol{U}}_{\boldsymbol{t}}$ (posterior means)



Notes: For $\widehat{U}_t$ see (26) and (23). (a) ≥ 3 loans, (b) ≥ 2 loans.