

# 1 Determinants of small business default\*

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## Abstract

In this paper, we empirically validate the importance of owner and business credit risk characteristics in determining default behaviour of more than 31 000 small business loans by type and size. Our results indicate that both *owner*- and *firm*-specific characteristics are important predictors of overall small business default. However, owner characteristics are more important determinants of small business *loans* but not small business *lines*. We also differentiate between small and large business accounts. The results suggest that owner scores are better predictors of small firm default behaviours, whereas firm scores are better predictors of large firm default behaviour.

## 1. Introduction

In this chapter, we develop a small business default model to empirically validate the importance of *owner* and the *business* credit bureau scores while controlling for time to default, loan contract structure as well as macroeconomic and industry risk characteristics. In addition, several unique features associated with the dataset enable us to validate the importance of the owner and business credit bureau scores in predicting the small business default behaviour of (i) spot market loans versus credit lines and (ii) small businesses below \$100 000 versus between \$100 000 and \$250 000.

Financial institutions regularly validate credit bureau scores for several reasons. First, bureau scores are generally built on static data, i.e. they do not account for the time to delinquency or default.<sup>1</sup> Second, bureau scores are built on national populations. However, in many instances, the target populations for the bureau scores are region-specific. This can cause deviation in the expected and actual performance of the scores. For example, customers of a certain region might be more sensitive to business cycles and so the scores in that region might behave quite differently during a recession. Third, the

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bureau scores may not differentiate between loan type (spot loans versus lines of credit) and loan size (below \$100K and above \$100K), i.e. they are designed as one-size-fits-all.

However, it is well documented that there are significant differences between bank spot loans (loans) and lines of credit (lines). For example, Strahan (1999) notes that firms utilize lines of credit to meet short-term liquidity needs, whereas spot loans primarily finance long-term investments. Agarwal *et al.* (2006) find that default performance of home equity loans and lines differ significantly. Hence, we assess whether there are any differences in the performance of small business loans and lines, and if so, what factors drive these differences?

Similarly, Berger *et al.* (2005) argue that credit availability, price and risk for small businesses with loan amounts below and above \$100K differ in many respects. Specifically, they suggest that scored lending for loans under \$100K will increase credit availability, pricing and loan risk; they attribute this to the rise in lending to ‘marginal borrowers’. However, scored lending for loans between \$100K and \$250K will not substantially affect credit availability, lower pricing and lesser loan risk. This is attributed to the price reduction for the ‘non-marginal borrowers’. Their results suggest that size does affect loan default risk.

Overall, our results indicate that a business owner’s checking account balances, collateral type and credit scores are key determinants of small business default. However, there are significant differences in economic contributions of these risk factors on default by credit type (loans versus lines) and size (under \$100K versus \$100K–250K). We find that the effect of owner collateral is three times as much on default for small business loans than for lines. This result is consistent with Berger and Udell’s (1995) argument that a line of credit (as opposed to loan) measures the strength of bank–borrower relationship, and as the bank–firm relationship matures, the role of collateral in small business lending becomes less important. Our results also show that the marginal impact of a 12-month increase in the age of the business on lowering the risk of a small business defaulting is 10.5% for lines of credit, but only 5.8% for loans. Moreover, a \$1000 increase in the 6-month average checking account balance lowers the risk of default by 18.1% for lines of credit, but only 11.8% for loans. Finally, although both owner and firm credit scores significantly predict the risk of default, the marginal impacts on the types of credits differ considerably. The marginal impact of a 10-point improvement in the *owner* credit score on lowering the risk of defaults is 10.1% for lines, but only 6.3% for loans. A similar 10-point improvement in the *firm* credit score lowers the risk of default by 6.3% for small business loans, but only 5.2% for small business lines. These results are consistent with that of Agarwal *et al.* (2006).

Comparing small businesses under \$100K (small) and those between \$100K and \$250K (large), we find that the marginal impact of a 10-point improvement in the owner credit score in lowering the risk of default is 13.6% for *small* firms, but only 8.1% for *large* firms. On the contrary, the marginal impact of a 10-point improvement in the firm credit score in lowering the risk of default is only 2.2% for *small* firms, but 6.1% for the *larger* size firms. Furthermore, a \$1000 increase in the 6-month average checking account balance lowers the risk of default by 5.1% for *small* firms, but by 12.4% for *large* firms. These results suggest that smaller size firms behave more like consumer credits, whereas larger size firms behave more like commercial credits and so bank monitoring helps account performance. These results are consistent with that of Berger *et al.* (2005).

The rest of the chapter is organized as follows. Section 1.2 discusses the data, methodology and summary statistics. Section 1.3 presents the empirical results for small business defaults by type (Section 1.3.1) and size (Section 1.3.2). Section 4 provides concluding remarks.

## 2. Data, methodology and summary statistics

### 2.1. Data

The data employed in this study are rather unique. The loans and lines are from a single financial institution and are proprietary in nature. The panel dataset contains over 31 000 small business credits from January 2000 to August 2002.<sup>2</sup> The majority of the credits are issued to single-family owned small businesses with no formal financial records. Of the 31 303 credits, 11 044 (35.3%) are *loans* and 20 259 (64.7%) are *lines* and 25 431 (81.2%) are under \$100K and 5872 (18.8%) are between \$100K and \$250K. The 90-day delinquency rate for our dataset of loans and lines are 1.6% and 0.9%, respectively. The delinquency rates for credits under \$100K and between \$100K and \$250K are 1.5% and 0.92%, respectively. It is worth mentioning some of the other key variables of our dataset. First, our dataset is a loan-level as opposed to a firm-level dataset. More specifically, we do not have information of all the loans a firm might have with other banks. Second, because these are small dollar loans, the bank primarily underwrites them based on the owners' credit profile as opposed to the firms credit profile. However, the bank does obtain a firm-specific credit score from one of the credit bureaus (Experian).<sup>3</sup> The owner credit score ranges from 1 to 100 and a lower score is a better score, whereas the firm credit score ranges from 1 to 200 and a higher score is a better score.

### 2.2. Methodology

For the purpose of this study, we include all accounts that are open as of January 2000, and exclude accounts with a flag indicating that the loan is never active, closed due to fraud/death, bankruptcy and default.<sup>4</sup> Furthermore, we also exclude all accounts that were originated before 1995 to simplify the analysis on account age. We follow the performance of these accounts from January 2000 for the next 31 months (until August 2002) or until they default.

We use a proportional hazard model to estimate the conditional probability of a small business defaulting at time  $t$ , assuming the small business is current from inception up to time  $t - 1$ . Let  $D_{i,t}$  indicate whether an account  $i$  defaults in month  $t$ . For instance, the business could default in month 24, then  $D_{i,t} = 0$  for the first 23 months and  $D_{i,24} = 1$ , and the rest of the observations will drop out of the sample. We define default as two cycles of being delinquent, as most accounts that are two cycles delinquent (i.e. 60 days past due) will default or declare bankruptcy. Furthermore, according to the SBRMS report, 57% of banks use the two cycles delinquent as their standard definition of default and another 23% use one cycle delinquent as their definition of default.<sup>5</sup>

The instantaneous probability of a small business  $i$  defaulting in month  $t$  can be written as follows:

$$D_{i,t} = h_0(t) \exp(\beta' X_i(t)) \quad (1.1)$$

where  $h_0(t)$  is the baseline hazard function at time  $t$  (the hazard function for the mean individual  $i$ -th sample), we use age (number of months) of the account to capture ‘seasoning’<sup>6</sup> as a proxy for this baseline.  $X_i(t)$  is a vector of time-varying covariates;  $\beta$  is the vector of unknown regression parameters to be estimated; and  $\exp(\beta'X_i(t))$  is the exponential distribution specification that allows us to interpret the coefficients on the vector of  $X$  as the proportional effect of each of the exogenous variables on the conditional probability of ‘completing the spell’, e.g. small business loan terminating.

The time-varying exogenous variables (known as covariates) that are crucial to a small business’ decision to default can be classified into five main risk categories as follows:

$$\beta'X_{i,t} = \beta_1 Owner_{i,t-6} + \beta_2 Firm_{i,t-6} + \beta_3 LoanContract_{i,t} + \beta_4 Macro_{i,t-6} + \beta_5 Industry_{i,t-6} \quad (1.2)$$

where  $Owner_{i,t-6}$  represents specific characteristics of the owner that may be important in the risk of a small business defaulting, including owner credit score, owner collateral and average checking account balance.  $Firm_{i,t-6}$  represents firm-specific firm characteristics that may affect default risks of the firm, including credit score for the business, firm collateral and months in business.<sup>7</sup> Finally,  $LoanContract_{i,t-6}$  captures loan amount, risk premium spreads and internally generated behaviour score for the loan.  $Macro_{i,t-6}$  captures county unemployment rate as well as 9 state dummies.<sup>8</sup>  $Industry_{i,t-6}$  captures 98 two-digit SIC dummies.<sup>9</sup> Time-varying values of owner, firm, loancontract, macro and industry risks are lagged 6 months before default because of concerns about endogeneity. For instance, owner credit score at default would have severely deteriorated. This would bias our results towards the owner risk score being highly significant (reverse causality). Similarly, we want to control for unemployment rate before default and at the time of default.<sup>10</sup> The above explanatory variables are defined in Table 1.1. In addition, we also consider the expected sign on each coefficient estimate in Table 1.1 and provide some intuitions below.

### Owner risks

The use of owner’s personal assets as collateral<sup>11</sup> to secure a business enhances the creditor’s claims of new assets (see Berger and Udell, 1995). Owners using personal assets to secure the loans or lines are less likely to pursue unnecessary risky projects as there is more at stake; therefore, small businesses using owner collateral are less likely to default. Next, we control for the owner credit score. The higher the owner score, the riskier the business owner, i.e. higher the risk of default.<sup>12</sup> A 6-month average checking account balance captures the liquidity position of a business owner. We expect this owner characteristic to be inversely related to default.<sup>13</sup>

### Firm risks

Like owner collateral, firm collateral merely alters the claims of the creditors (Berger and Udell, 1995). Hence, firm collateral is expected to have negative impact on default risks. Similarly, firms with higher credit score are expected to be less risky and, thus, are less likely to default. Finally, a non-linear estimation for months in business should capture

Table 1.1 Variables, definitions and expected signs in the event of default

Variable	Definition	Expected Sign
<b>Owner risks</b>		
Owner collateral	Dummy variable indicating owner-specific collateral (mortgage, personal savings, etc.)	–
Owner score <sub><i>t-6</i></sub>	Quarterly updated score measuring owner credit risk characteristics – higher score high risk	+
Average 6 months checking account balance <sub><i>t-6</i></sub>	Six-month average checking account balance updated monthly	–
<b>Firm risks</b>		
Firm collateral	Dummy variable indicating firm-specific collateral (receivables, cash, etc.)	–
Firm score <sub><i>t-6</i></sub>	Quarterly updated score measuring firm credit risk characteristics – lower score high risk	–
Months in business	Months in business as reported by the credit bureau	+
Months in business (squared)		–
<b>Loan contract</b>		
Loan amount	Loan amount at origination	–
Interest rate spread <sub><i>t-6</i></sub>	Interest rate – prime rate	+
Internal risk rating <sub><i>t-6</i></sub>	Bank-derived risk rating for the loan	+
<b>Macro and industry risks</b>		
Unemployment rate <sub><i>t-6</i></sub>	County unemployment rate	+

the aging process of any business, and we expect the default rate to rise up to a certain age and then drop thereafter, i.e. younger accounts have a higher probability of default.

### *Contract structure*

Internal risk rating is a behavioural score based on the performance of the loan. The higher the behavioural score, the higher the risk of a small business defaulting. Loan amount determines the *ex post* risk characteristics of the owner and the business. A higher loan amount implies that both the business and/or the owner are lower risk, and thereby should reduce the risk of default. In other words, the bank perceives the borrower to be lower risk, and so, it is willing to provide a higher loan amount.

### *Macroeconomic risks*

We expect that small businesses facing higher local unemployment rate are subject to higher risks of default.

### *Industry risks*

Control for differing risk profile by SIC industry code.

**Table 1.2** Summary statistics for small business accounts by type and size

Variables	Type		Size	
	Loans	Lines	Small	Large
Number of accounts	11 044	20 259	25 431	5,872
Share of total	35.3%	64.7%	81.2%	18.8%
<b>Owner risks</b>				
Owner collateral	0.33	0.02	0.35	0.08
Owner score <sub><i>t-6</i></sub>	76	79	82	61
Average 6 months checking account Balance <sub><i>t-6</i></sub>	\$33 987	\$31 156	\$28 724	\$57 059
<b>Firm risks</b>				
Firm collateral	0.47	0.40	0.44	0.64
Firm score <sub><i>t-6</i></sub>	136	102	114	122
Months in business	135	109	116	145
<b>Loan contract</b>				
Loan amount	\$103 818	\$79 740	\$65 420	\$197 425
Loan interest rate	7.48	7.42	7.49	6.84
Internal risk rating <sub><i>t-6</i></sub>	5.19	5.14	5.17	5.07
<b>Macro and industry risks</b>				
Unemployment Rate <sub><i>t-6</i></sub>	5.25	5.22	5.23	5.22

### 2.3. Summary statistics

Table 1.2 provides summary statistics for some of the key variables. About 33% of the loans and 35% of the small firms have personal collateral, whereas lines and large firms have less than 10% personal collateral. Conversely, the lines and large firms have significant amount of firm collateral. Additionally, over 50% of the lines do not have any collateral. The loans amount is three times as much for the large businesses in comparison with the small businesses. Although not statistically significant, the internal credit ratings for the lines of credit and large businesses reflect lower risk in comparison with loans and small businesses.

## 3. Empirical results of small business default

We first estimate the baseline hazard, as discussed in Gross and Souleles (2002), using a semiparametric model to understand the default rate differences of same age accounts over calendar time and cohort by type and size segments. The semiparametric model estimation does not assume any parametric distribution of the survival times, making the method considerably more robust. The baseline survival curves for small business *loans* are statistically different than those for the *lines* (see Figure 1.1). The line sample exhibits a relatively higher survival rates (i.e. lower probability of default) with account age, but the loan sample exhibits a relatively lower survival rate (i.e. higher probability of default) with account age. Next, the baseline survival curves for small business credits between

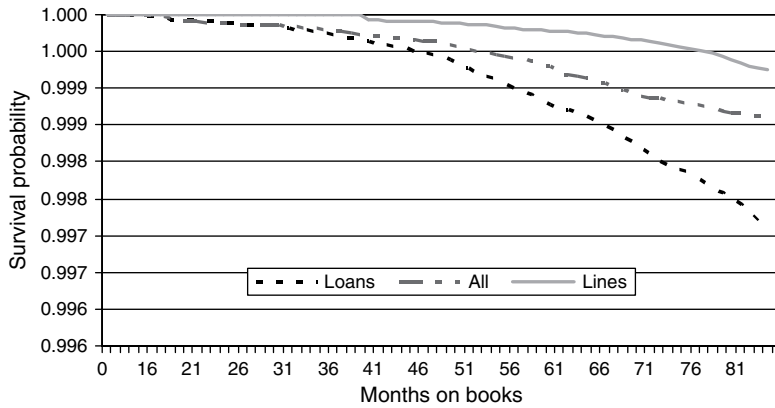


Figure 1.1 Survival curves for small business default by type

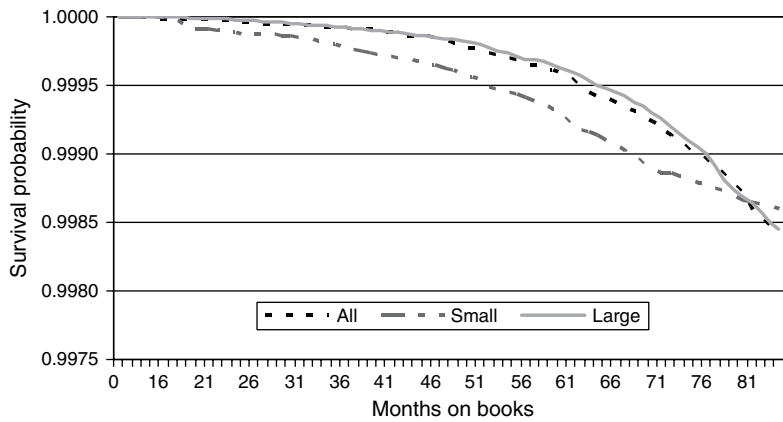


Figure 1.2 Survival curves for small business default by size

\$100K and \$250K are statistically different than those under \$100K (see Figure 1.2). The larger credits exhibit a relatively higher survival rate (i.e. lower probability of default) with account age, but the smaller credits exhibit a relatively lower survival rate (i.e. higher probability of default) with account age.

Next, we estimate Equation 1.1 to assess the various factors that may impact the likelihood of a small business defaulting. We also conduct exhaustive robustness test by including quadratic specifications for the various risk variables, discrete dummies for some of the continuous variable, log transformations and others.

We first estimate the conditional probability of lines defaulting and loans defaulting separately. Table 1.3 summarizes the estimated impact of owner and firm risk on the likelihood of a small business defaulting, while controlling for loan contract structure and macroeconomic and industry risks. Below, we discuss how lines and loans do respond differently to their determinants, particularly owner- and firm-specific factors.

Table 1.3 Determinants of small business default – loans and lines

Variable	Type					
	Loans			Lines		
	Coefficient Value	Std. Error	t-Statistics	Coefficient Value	Std. Error	t-Statistics
<b>Owner risks</b>						
Owner collateral	-0.97823	0.35498	-2.76	-1.89872	1.24876	-1.52
Owner score <sub><i>t-6</i></sub>	0.00103	0.00040	2.59	0.00299	0.00124	2.41
Average 6 months checking account balance <sub><i>t-6</i></sub>	0.00000	0.00000	-2.30	-0.00001	0.00000	-3.06
<b>Firm risks</b>						
Firm collateral	-1.93484	0.33299	-5.81	-1.10893	0.33289	-3.33
Firm score <sub><i>t-6</i></sub>	-0.00073	0.00033	-2.22	-0.00068	0.00023	-2.99
Months in business	0.00124	0.00340	0.36	0.04140	0.01239	3.34
Months in business (squared)	-0.00001	0.00000	-2.55	-0.00007	0.00002	-3.03
<b>Loan contract</b>						
Loan amount	0.00000	0.00000	-2.20	-0.00001	0.00000	-2.94
Risk premium <sub><i>t-6</i></sub>	0.05283	0.01839	2.87	2.53459	0.33289	7.61
Internal risk rating <sub><i>t-6</i></sub>	0.32349	0.04020	8.05	1.38989	0.13289	10.46
<b>Macro and industry risks</b>						
Unemployment rate <sub><i>t-6</i></sub>	2.49890	0.73495	3.40	0.68933	0.56757	1.21
Quarter dummy	Yes			Yes		
SIC dummy	Yes			Yes		
State dummy	Yes			Yes		
Log likelihood	-627			-578		
number of observations	298 230			547 026		

### 3.1. Default behaviours of loans versus lines

Our results show that owner characteristics are less predictive of line defaults in comparison with loan defaults. The use of the owner's personal assets to secure loans, as opposed to lines, reduces the likelihood of loans defaulting. The finding that owner collateral is not a significant determinant of default for small business lines of credit is consistent with Berger and Udell (1995). Furthermore, a deterioration in the owner's as well as the firm's credit risk significantly raises the default risks of small businesses; however, the marginal impact varies between credit types. In Table 1.4, we show that the impact of a 10-point increase in the owner credit score (a deterioration of the credit risk of the owner) raises the default probability by 10.1% for loans, but only 6.3% for lines. On the contrary, a 10-point decline in the firm credit score (a deterioration of the credit risk of the firm) raises the default probability by 6.3% for loans, but only 5.2% for lines.

Moreover, we find that both owner and firm collateral are better predictor of default for loans than for lines. Owner collateral lowers the risk of default by 8.3% for loans, but only 2.9% for lines. Similarly, firm collateral lowers the risk of default by 4.4% for loans, but only 1.4% for lines.

Table 1.4 Marginal effects of owner and firm characteristics on small business default

Variables	Type		Size	
	Loans (%)	Lines (%)	Small (%)	Large (%)
<b>Owner risks</b>				
Owner collateral	-8.3	-2.9	-2.2	-5.9
10 Point rise in owner score <sub><i>t-6</i></sub>	10.1	6.3	13.6	8.1
\$1000 Increase in average 6 months checking account balance <sub><i>t-6</i></sub>	-11.8	-18.1	-5.1	-12.4
<b>Firm risks</b>				
Firm collateral	-4.4	-1.4	-0.7	-2.3
10 point drop in firm score <sub><i>t-6</i></sub>	6.3	-5.2	2.2	6.1
12 Months rise of months in business	-5.8	-10.5	-7.9	-13.1

Equally important, the results show that the number of months in business is significantly positive, with the quadratic term significantly negative, for lines of credit. Small businesses that have been in business for an additional 1 year have a lower probability of default by 5.8% and 10.5%, respectively, for loans and lines. This result suggests that younger firms face higher risk of defaulting. However, the number of months in business is statistically insignificant in determining loan defaults. This would imply that even with age, loans are inherently more risky than lines.

The 6-month average checking account balance is highly significant in determining the default risks of lines and loans. However, the marginal impact of a \$1000 rise in average checking account balance lowers the probability of default by 18% for lines, but only by 11% for loans. These results support the Mester *et al.* (forthcoming) argument that 'banks are special'.

### 3.2. Default behaviours of small versus large credits

We investigate whether default behaviours of credits differ between small businesses with less than \$100K (small) and those with debt between \$100K and \$250K (large). Table 1.5 summarizes the estimated coefficients of small business default for small and large debt accounts. These results are very interesting and provide evidence that small businesses under and over \$100K have very different risk characteristics, as discussed below.

The risks of default between small businesses with credit amount of less than \$100K and those with credit amount between \$100K and \$250K mainly differ in owner characteristics. For example, although both owner and firm collateral significantly reduce the likelihood of default, the impact is more striking for firms with credit amount between \$100K and \$250K (large) than for firms with credit amount less than \$100K (small). Specifically, the use of owner collateral lowers the risk of default of large firms by 5.9%, but of small firms by only 2.2%. Similarly, the use of firm collateral lowers the risk of default of large firms by 2.3%, but of small firms by only 0.7%.

Furthermore, our results suggest that owner-specific score may be a better predictor of small firm default risks, whereas firm-specific score is a better predictor of large firm default behaviours. The reason lies in the magnitude of the marginal impact. For example, a 10-point increase in owner score (a deterioration in the owner's credit risk) raises the

Table 1.5 Determinants of small business default – small and large

Variable	Size					
	Small			Large		
	Coefficient Value	Std. Error	t-Statistics	Coefficient Value	Std. Error	t-Statistics
<b>Owner risks</b>						
Owner collateral	-0.33875	0.13489	-2.51	-8.32895	3.32478	-2.51
Owner score <sub>t-6</sub>	0.00009	0.00004	2.31	0.23885	0.06924	3.45
Average 6 months checking account balance <sub>t-6</sub>	-0.00001	0.00000	-2.12	-0.00001	0.00000	-2.83
<b>Firm risks</b>						
Firm collateral	-3.23899	0.44389	-7.30	-9.2381	6.7744	-1.36
Firm score <sub>t-6</sub>	-0.00074	0.00034	-2.15	-0.00079	0.00039	-2.03
Months in business	0.00124	0.00798	0.16	0.02878	0.03848	0.75
Months in business (squared)	-0.00003	0.00001	-2.41	-0.00007	0.00003	-2.24
<b>Loan contract</b>						
Loan amount	-0.00001	0.00000	-4.67	-0.00001	0.00000	-3.50
Risk premium <sub>t-6</sub>	0.04898	0.03289	1.49	0.33589	0.08327	4.03
Internal risk rating <sub>t-6</sub>	0.54899	0.06325	8.68	0.73298	0.23775	3.08
<b>Macro and industry risks</b>						
Unemployment rate <sub>t-6</sub>	0.13295	0.29835	0.45	0.03893	0.98355	0.04
Quarter dummy	Yes			Yes		
SIC dummy	Yes			Yes		
State dummy	Yes			Yes		
Log likelihood	-984			-591		
Number of observations	686 347			158 908		

probability of default by 13.6% for small credits and only by 8.1% large credits. On the contrary, a 10-point decline in firm score (a deterioration in the firm's credit risk) raises the probability of default by 2.2% for small credits, but by 6.1% for large credits. These results suggest that small credits behave more like consumer credits, whereas large credits behave more like commercial credits.

#### 4. Conclusion

We empirically validate the importance of *owner* versus *firm* credit bureau score in determining default behaviours of small business loans, while controlling for time to default, the loan contract structure as well as macroeconomic and industry risks. We also compare and contrast the impact of *owner* and *firm* characteristics on small business default by type (loans versus lines) and size (under \$100K versus \$100K and \$250K).

Our results indicate that both *owner*- and *firm*-specific characteristics are important predictors of overall business default. However, the economic impacts of owner

characteristics significantly differ for small business *loans* than for *lines*. The marginal impact of owner collateral, owner credit risk improving and owner–bank relationship strengthening in lowering the risks of default is considerably larger for loans than for lines.

When we differentiate between small and large business accounts, our results suggest that the economic impact of owner and firm characteristics on small business default also differ considerably. For example, the marginal impact of an owner credit risk deteriorating on the probability of default is larger for small firms, whereas the marginal impact of a firm credit risk deteriorating on the probability of default is larger for large firm.

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## Notes

1. Credit bureau scores are built on historic data. The datasets are typically collected over a 12-month period with performance data for additional 24 months.
2. We very much liked to include a longer time period; unfortunately, data were not available. However, our data cover both the latter part of an economic growth and the early part of an economic recession. Moreover, as discussed in Berger and Udell (1998), an estimated 23.7% (52.7%) of small businesses disappear within the first 2 (4) years because of default/bankruptcy and other reasons. Hence, we should capture a sufficient number of defaults within the 2-year sample period (4 years in business because a business had to be operational for at least 18 months to qualify for a loan).
3. See, [www.experian.com](http://www.experian.com)
4. As discussed in Gross and Souleles (2002), this “makes the data stationary.” We conduct robustness tests by excluding accounts that default in the first 2 months since January 2000. The results are qualitatively the same.
5. For the purpose of this study, alternate definitions of default were also considered. Specifically, we defined default as 90 days past due and the results are robust to the definition of default.
6. Loan age “account seasoning” is modelled as a polynomial also discussed by Gross and Souleles (2002). The Cox Model does not explicitly report the coefficient values for the loan age variable, but the survival curves do provide the impact of account seasoning in small business default.
7. Months in business does not necessarily equal to loan age. As over 90% of the accounts in the dataset have been in business anywhere from 6 months to 24 months before applying for a loan at the financial institution.
8. Our data are primarily from the ten New England states. The dummies control for any states laws or state-specific macro economic polices.

9. For the purposes of this study, we interact the state and SIC dummy variables so that we have a state-specific control variable for the same SIC across states. This will help isolate any state-specific effect on a particular two-digit SIC code.
10. A related issue is the appropriate lag structure for these variables. As discussed in Gross and Souleles (2002), we could choose to lag these variables at account origination date, but that would not necessarily control for the risk composition between time of origination and the time since the beginning of the sample. Next, we could choose to control them at the time since the beginning of the sample or lag them 12 months from the time at default. We tried both these specifications, and the results are qualitatively the same.
11. There are over 70 distinct categories of collateral, but we have classified them into three broad categories, namely no collateral, owner collateral (residential mortgage, taxi medallions, stocks and bonds, bank deposits, gold/silver, etc.) and firm collateral (machinery, equipment, inventory, accounts receivable, letters of credit, etc.). This segmentation is consistent with Berger and Udell (1995, pp. 357) who describe owner and firm collateral as “outside” and “inside” collateral, respectively.
12. The score is counterintuitive, since traditional scores such as FICO lower risk with higher scores. This score is developed by Experian.
13. Mester, Nakamura and Renault (forthcoming) also conclude that checking account information does provide a “relatively transparent window” in predicting small business credit deterioration. Evidence of a negative relationship between default and checking account balance.