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Defaults on government guaranteed loans by potential high growth firms: Evidence from the COVID-19 period

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ABSTRACT

Equity finance is used to fund innovative and growth-oriented businesses because of its resilience during economic downturns and investors' willingness to undertake higher risks compared to other financing. During the pandemic, 6500 equity-funded firms obtained government-guaranteed loans from traditional banks and new lenders. Our analysis of the determinants of loan default revealed that new lenders experienced a significantly higher default rate than the main banking sector. Additionally, firms funded by equity crowdfunding have a higher loan default rate than those backed by other equity providers. We explore the factors influencing defaults and variations by lender and investor type.

1. Introduction

Equity finance is a crucial aspect of funding for potentially high-growth and innovative companies, making it a key driver of long-term economic growth. However, this vital segment of business has faced 'market failures' in access to funding due to information asymmetries and misalignment between investors and investees, resulting in equity gaps (Wilson et al., 2018). The COVID-19 crisis potentially exacerbated the situation, as it represented an unprecedented shock to the entire economy and posed challenges for companies heavily reliant on equity finance, seeking follow-on funding from existing or new investors. Exploring a unique database of a subset of the guaranteed loans portfolio administered in response to the crisis, we model loan defaults by equity-backed firms in relation to borrower characteristics, lender, and investor types.

The UK implemented various measures to support small and medium-sized enterprises (SMEs) in response to the pandemic. This included the launch of several business loan schemes, such as the Bounce Back Loan Scheme (BBLS), Coronavirus Business Interruption Loan Scheme (CBILS), and Coronavirus Large Business Interruption Loan Scheme (CLBILS). These loans were administered by a range of lenders, including traditional banks and new entrants. Since the global financial crisis, the UK government has been committed to stimulating the growth of a diverse pool of lenders in the financial services sector, particularly SMEs. This has resulted in the growth of challenger banks, alternative financing, and fintech. For instance, by 2019, challenger banks and other specialist lenders had achieved a 50 % share of total gross bank lending to SMEs (British Business Bank, 2020). Few studies have examined the role of new entrants in the SME landscape, such as challenger banks and alternative finance. Moreover, the existing literature has explored various aspects of guaranteed loans (Glennon and Nigro, 2005; Caselli et al., 2021; Cowling et al., 2024) but, with the exception of crowd funded ventures (Kazembalaghi et al., 2024), the important subsample of equity-funded companies has been overlooked. These high-growth potential firms primarily depend on equity financing rather than debt to support their initial development and growth phases. Consequently, they are particularly vulnerable in periods of crisis and heightened investor uncertainty. We expect that firms that utilise guaranteed loans without the active support of an equity investor through the crisis will be more vulnerable to default. The study examines a wide spectrum of equity-backed firms which we categorise by investor type. Our research aims to address gaps in the literature by examining whether lender and investor types explain variations in the pattern of loan default in the potential high-growth sector of SMEs.

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Table 1
Sample Selection Steps.

		Companies
Loans issued under BBLS, CBILS or CLBILS for equity funded companies	7818	
Less		
Loans for companies without last available accounts between 1/4/2017 and 31/3/2020	−200	
Loans for companies that became insolvent before 31/3/2020	−7	
Loans with missing values for explanatory variables	−1008	
Loans for companies from Northern Ireland	−103	
Final estimation sample	**6500**	5791

Notes: The table shows the steps involved in the preparation of the estimation sample. The unit of analysis is the loan. The sample includes covid loans issued under BBLS, CBILS or CLBILS for all eligible companies with an equity deal at the beginning of the covid period (31 March 2020).

In line with previous literature on guaranteed loans (Cowling et al., 2024), we hypothesize that the guaranteed loans for equity funded companies issued by challenger banks and other new market entrants, who could attract new business and expand their market share without risk of loss, will exhibit higher risk and a greater propensity for default (H1). Second, with respect to investor types, we posit that firms supported by equity investors who do not actively engage in providing expertise or monitoring will demonstrate a higher default rate on these guaranteed loans (H2). Third, we anticipate that the BBLS, characterised by its 100 % coverage, low interest rates, and absence of required credit checks, creates moral hazard for lenders, and will be correlated with a higher default rate (H3).

2. Data and methodology

The dataset covers 6500 guaranteed loans for equity funded companies, i.e., companies that received at least one round of external equity

Table 2
Descriptive statistics.

	Whole sample (N = 6500)					Defaulted	Non-defaulted		
Variable name	Mean	SD	Min	Median	Max	Mean	Mean	*p*-value	Cohen’s D
Bank Lender Indicator	0.85	0.36	0	1	1	0.81	0.85	0.003***	0.112
Challenger Bank Indicator	0.07	0.26	0	0	1	0.15	0.06	0.000***	−0.326
Other Lender Indicator	0.08	0.27	0	0	1	0.04	0.09	0.000***	0.157
Venture Capital (VC)	0.14	0.35	0	0	1	0.11	0.15	0.002***	0.117
Business Angel (BA)	0.12	0.32	0	0	1	0.08	0.12	0.002***	0.117
Equity Crowd Funding (ECF)	0.09	0.29	0	0	1	0.14	0.09	0.000***	−0.196
Government VC (GVC)	0.06	0.25	0	0	1	0.04	0.07	0.000***	0.135
Foreign VC (FVC)	0.04	0.19	0	0	1	0.03	0.04	0.084*	0.066
Loan to Turnover	0.21	2.20	0.00	0.14	162.45	0.18	0.21	0.725	0.014
BBLS Indicator	0.75	0.43	0	1	1	0.90	0.73	0.000***	−0.390
LN(Age at loan in days)	7.76	0.66	5.54	7.76	10.67	7.57	7.78	0.000***	0.325
Indicator of loan in 2020	0.88	0.32	0	1	1	0.94	0.87	0.000***	−0.191
Seed Stage of Investment	0.53	0.50	0	1	1	0.69	0.51	0.000***	−0.357
Venture Stage of Investment	0.33	0.47	0	0	1	0.25	0.34	0.000***	0.196
Growth Stage of Investment	0.07	0.26	0	0	1	0.04	0.07	0.000***	0.140
Established Stage of Investment	0.07	0.25	0	0	1	0.02	0.07	0.000***	0.197
Announced Deal	0.34	0.47	0	0	1	0.31	0.34	0.128	0.058
Working Capital to Total Assets	−0.08	0.97	−3.15	0.16	1.00	−0.45	−0.03	0.000***	0.438
Current Assets to Total Assets	0.73	0.30	0.01	0.86	1.00	0.70	0.73	0.019**	0.090
Profit/Loss Account Reserve to Total Assets	−1.08	1.62	−4.18	−0.44	1.00	−1.61	−1.01	0.000***	0.375
Short and Long-term Debt to Total Assets	0.20	0.28	0	0.04	0.83	0.23	0.19	0.001***	−0.128
LN(Total Assets)	12.76	1.85	0	12.84	17.43	11.93	12.87	0.000***	0.519
LN(Total Assets) squared	166.43	46.45	0	164.96	388.34	145.82	169.20	0.000***	0.510
Ex-ante Risk Score	0.03	0.04	0	0.02	0.43	0.04	0.03	0.000***	−0.136
Missing Risk Score	0.05	0.22	0	0	1	0.05	0.05	0.501	0.026
Sector (Media)	0.08	0.28	0	0	1	0.09	0.08	0.518	−0.025
Sector (Industrial)	0.29	0.46	0	0	1	0.31	0.29	0.434	−0.030
Sector (Infrastructure)	0.04	0.20	0	0	1	0.05	0.04	0.493	−0.026
Sector (Retail)	0.09	0.29	0	0	1	0.09	0.09	0.950	−0.002
Sector (Crafts)	0.02	0.15	0	0	1	0.03	0.02	0.459	−0.028
Sector (Leisure)	0.15	0.36	0	0	1	0.20	0.15	0.001***	−0.131
Sector (Supply Chain)	0.03	0.17	0	0	1	0.03	0.03	0.745	−0.012
Sector (Professional services)	0.42	0.49	0	0	1	0.38	0.43	0.010***	0.099
Sector (Trades)	0.02	0.13	0	0	1	0.02	0.02	0.711	−0.014
Sector (Personal services)	0.09	0.29	0	0	1	0.10	0.09	0.407	−0.032
Sector (Technology)	0.42	0.49	0	0	1	0.44	0.42	0.199	−0.049
Sector (Energy)	0.02	0.14	0	0	1	0.02	0.02	0.454	0.029
East Midlands	0.03	0.18	0	0	1	0.03	0.03	0.635	0.018
East of England	0.07	0.25	0	0	1	0.06	0.07	0.619	0.019
London	0.42	0.49	0	0	1	0.46	0.41	0.008***	−0.102
North East	0.03	0.17	0	0	1	0.02	0.03	0.270	0.042
North West	0.07	0.26	0	0	1	0.09	0.07	0.112	−0.061
Scotland	0.06	0.23	0	0	1	0.04	0.06	0.046**	0.077
South East	0.13	0.34	0	0	1	0.11	0.14	0.034**	0.082
South West	0.08	0.27	0	0	1	0.09	0.08	0.450	−0.029
Wales	0.03	0.16	0	0	1	0.02	0.03	0.411	0.032
West Midlands	0.04	0.19	0	0	1	0.04	0.04	0.449	−0.029
Yorkshire and The Humber	0.04	0.20	0	0	1	0.03	0.04	0.066*	0.071

The statistical significance is denoted by asterisks (* $p < 10$ %, ** $p < 5$ %, *** $p < 1$ %).

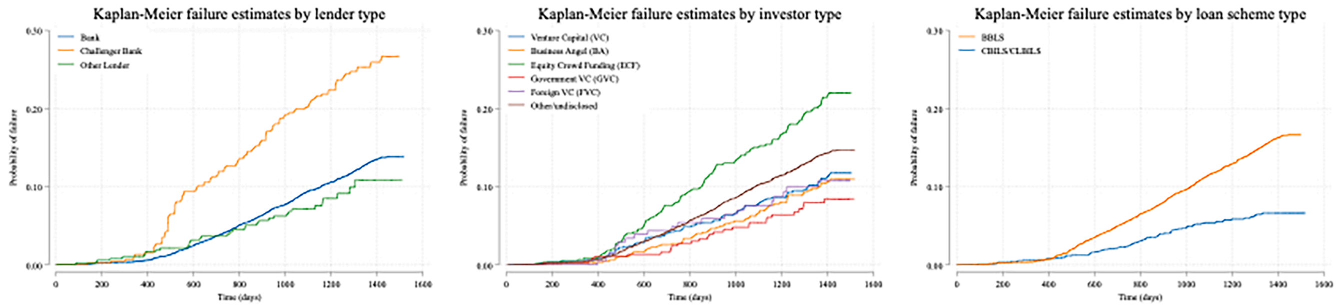

Fig. 1. Kaplan-Meier failure estimates.

Table 3
Cox proportional hazard models.

	(1) Default hazard	(2) Default hazard	(3) Default hazard
Challenger Bank Indicator	0.751***	0.649***	0.649***
Other Lender Indicator	−0.178	0.633***	0.626***
Venture Capital (VC)	−0.168	0.00124	0.00575
Business Angel (BA)	−0.288**	−0.175	−0.174
Equity Crowd Funding (ECF)	0.531***	0.533***	0.487***
Government VC (GVC)	−0.438**	−0.301	−0.323
Foreign VC (FVC)	−0.106	−0.0164	−0.0481
Loan to Turnover		−0.0270	−0.0248
BBLS Indicator		0.548***	0.546***
LN(Age at loan in days)		−0.0726	−0.0567
Indicator of loan in 2020		0.104	0.112
Venture Stage of Investment		−0.184*	−0.184*
Growth Stage of Investment		−0.0970	−0.0992
Established Stage of Investment		−0.481*	−0.474*
Announced Deal		−0.0620	−0.0422
Working Capital to Total Assets		−0.0903**	−0.0934**
Current Assets to Total Assets		−0.644***	−0.611***
Profit/Loss Account Reserve to Total Assets		−0.0360	−0.0340
Short and Long-term Debt to Total Assets		0.0994	0.114
LN(Total Assets)		0.135	0.161
LN(Total Assets) squared		−0.0121**	−0.0133**
Ex-ante Risk Score		5.099***	4.956***
Missing Risk Score		0.255	0.246
Industry sector indicators	No	No	Yes
Regional indicators	No	No	Yes
Number of observations	6500	6500	6500
Number of defaulted loans	769	769	769
McFadden pseudo R^2	0.00702	0.0232	0.0254

The table shows the estimation results for the Cox's proportional hazard models. The statistical significance of the individual estimated coefficients is based on robust standard errors and is indicated with asterisks (*, **, and *** denote statistical significance at 10 %, 5 %, and 1 % level, respectively).

funding before the onset of the COVID-19 crisis (31 March 2020). There are 769 defaulted loans in the dataset. The details of sample selection steps are presented in Table 1.

In line with the previous literature (Fenech et al., 2016; Caselli et al., 2021; Goedecke, 2018; Cowling et al., 2024), we use Cox proportional hazard model to examine the relationship between loan default and explanatory variables. The dependent variable is specified such that the loan time starts at its origination date and ends on default date. For loans that have not defaulted by the end of the sample period (11 June 2024), the dependent variable is censored at this point.

The model specification follows studies exploring other loan guarantee schemes (Caselli et al., 2021; Glennon and Nigro, 2005; Cowling et al., 2024), and those on new firm survival (Van Praag, 2003; Audretsch and Mahmood, 1995). The hazard models allow us to estimate the risk of loan default as a function of firm characteristics, demographics, and loan contract parameters. The Cox model is expressed by the hazard function $h(t)$ which can be interpreted as instantaneous risk of default occurrence:

$$\begin{aligned} h(t) = h_0(t)\ \exp\big(&Lender\_type_i^T\alpha_1 + Investor\_type_i^T\alpha_2 \\ &+ COVID\_loan\_variables_i^T\alpha_3 + Equity\_deal\_variables_i^T\alpha_4 \\ &+ Financial\_ratios_i^T\alpha_5 + Non\_financial\_variables_i^T\alpha_6 + Fixed\_effects_i^T\alpha_7\big) \end{aligned} \quad (1)$$

Table 4
Profile of lender categories.

	(1) Banks	(2) Challenger banks	(3) Other Lenders
Venture Capital (VC)	0.201	−0.175	0.0494
Business Angel (BA)	0.289**	−0.378*	−0.172
Equity Crowd Funding (ECF)	0.186	−0.283	0.0621
Government VC (GVC)	0.119	−0.659*	−0.256
Foreign VC (FVC)	−0.275	0.151	0.524*
Loan to Turnover	0.0124	0.00355	0.00816
BBLS Indicator	1.998***	1.197***	−5.337***
LN(Age at loan in days)	0.327***	−0.774***	0.369***
Indicator of loan in 2020	0.878***	−0.454***	−1.007***
Venture Stage of Investment	−0.168*	0.190	−0.0802
Growth Stage of Investment	−0.166	−0.192	0.0551
Established Stage of Investment	−0.0760	0.256	−0.477*
Announced Deal	−0.319**	0.268	0.402*
Working Capital to Total Assets	−0.110*	0.126*	0.125
Current Assets to Total Assets	0.267*	−0.376**	−0.195
Profit/Loss Account Reserve to Total Assets	−0.0362	−0.00486	0.0653
Short and Long-term Debt to Total Assets	−0.0941	−0.0521	0.738***
LN(Total Assets)	0.0189	−0.478***	2.770***
LN(Total Assets) squared	0.00796	0.0151**	−0.111***
Ex-ante Risk Score	−3.164***	2.807**	3.271*
Missing Risk Score	−0.190	0.213	0.293
Constant	−4.806***	6.787***	−19.43***
Industry sector indicators	Yes	Yes	Yes
Regional indicators	Yes	Yes	Yes
Number of observations	6500	6500	6500
Number of loans issued by given lender	5498	467	535
McFadden pseudo R^2	0.143	0.108	0.470
Area under ROC curve	0.764	0.750	0.944

The table shows the estimation results for the models profiling individual lender categories. The models are estimated using binary logistic regression and the dependent variable in both models is the indicator of specific lender category. The categorisation of the lenders into lender categories is described in Appendix B. The statistical significance of the individual estimated coefficients is based on robust standard errors and is indicated with asterisks (*, **, and *** denote statistical significance at 10 %, 5 %, and 1 % level, respectively).

Table 5
Accelerating failure time (AFT) models.

	Exponential (1) Time to default	Log-logistic (2) Time to default	Weibull (3) Time to default	Log-normal (4) Time to default	Gamma (5) Time to default
Challenger Bank Indicator	−0.623***	−0.393***	−0.350***	−0.427***	−0.423***
Other Lender Indicator	−0.558**	−0.346***	−0.341***	−0.365***	−0.362***
Venture Capital (VC)	−0.00779	0.000174	−0.00395	−0.0132	−0.0119
Business Angel (BA)	0.170	0.105	0.0903	0.137	0.134
Equity Crowd Funding (ECF)	−0.472***	−0.283***	−0.256***	−0.307***	−0.304***
Government VC (GVC)	0.317	0.177	0.172	0.175	0.175
Foreign VC (FVC)	0.0564	0.0152	0.0235	0.0439	0.0403
Loan to Turnover	0.0239	0.0130	0.0123	0.0166	0.0161
BBLS Indicator	−0.563***	−0.272***	−0.280***	−0.266***	−0.266***
LN(Age at loan in days)	0.0509	0.0309	0.0258	0.0393	0.0384
Indicator of loan in 2020	−0.173	−0.0129	−0.0131	−0.00597	−0.00610
Venture Stage of Investment	0.182*	0.0989*	0.100*	0.107*	0.106*
Growth Stage of Investment	0.118	0.0412	0.0563	0.0288	0.0305
Established Stage of Investment	0.460*	0.245*	0.255*	0.205	0.209
Announced Deal	0.0429	0.0161	0.0207	0.0130	0.0136
Working Capital to Total Assets	0.0852**	0.0518**	0.0492**	0.0469*	0.0477*
Current Assets to Total Assets	0.600***	0.348***	0.323***	0.361***	0.360***
Profit/Loss Account Reserve to Total Assets	0.0368	0.0204	0.0184	0.0266	0.0260
Short and Long-term Debt to Total Assets	−0.113	−0.0582	−0.0572	−0.0617	−0.0616
LN(Total Assets)	−0.171	−0.0631	−0.0779	−0.0146	−0.0205
LN(Total Assets) squared	0.0138**	0.00627*	0.00671**	0.00420	0.00444
Ex-ante Risk Score	−4.874***	−2.831***	−2.639***	−3.185***	−3.137***
Missing Risk Score	−0.238	−0.144	−0.132	−0.135	−0.135
Constant	9.398***	7.950***	8.214***	7.785***	7.825***
Industry sector indicators	Yes	Yes	Yes	Yes	Yes
Regional indicators	Yes	Yes	Yes	Yes	Yes
Number of observations	6500	6500	6500	6500	6500
Number of defaulted loans	769	769	769	769	769
Akaike Information criterion - AIC	5173.1	4864.9	4885.2	4847.0	4848.8

The table shows the estimation results for the accelerating failure time (AFT) models where the dependent variable is time to failure (logarithm). The assumed distribution of random errors is shown in the first row. The statistical significance of the individual estimated coefficients is based on robust standard errors and is indicated with asterisks (*, **, and *** denote statistical significance at 10 %, 5 %, and 1 % level, respectively).

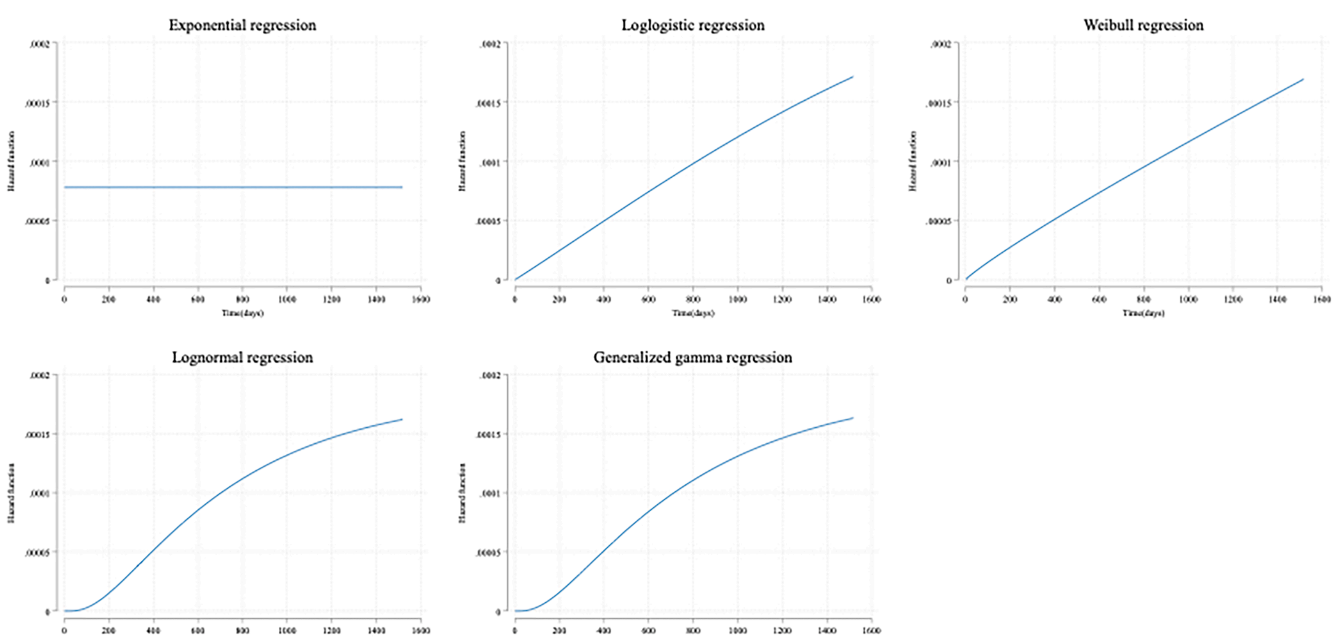

Fig. 2. Baseline hazard functions for AFT models presented in Table 5.

where $h_0(t)$ is baseline hazard function. *Lender type* variables include indicators of challenger banks and other lenders[1] (bank lender is the reference category), *Investor type* variables include indicators of venture capital (VC), business angels (BA), equity crowdfunding (ECF), government venture capital (GVC) and foreign venture capital (FVC).[2] *COVID loan variables* include the loan-to-turnover ratio, BBLS indicator, company age at loan origination date (logarithm), and indicator of loans issued in 2020. *Equity deal variables* include stage of evolution (venture, growth or established with seed as a reference category) and indicator of announced deals. The vector of *Financial ratios* includes liquidity (working capital to total assets and current assets to total assets), rentability (profit and loss account reserve to total assets), and leverage measures (short-term loans and bank overdraft to total assets). *Non-financial variables* comprise size (logarithm of total assets and its square) and ex-ante risk score, along with the indicator if the risk score is missing. Finally, the *Fixed effects* include industry sector and regional indicators. The variables are defined in Appendix A. Appendix B and C provide details on lender types categories and correlations between variables used in the analysis, respectively.

3. Empirical results

Table 2 displays descriptive statistics of the explanatory variables used in our loan default analysis, and Fig. 1 shows Kaplan-Meier failure estimates for COVID loans in the UK for equity-funded companies. Table 3 reports the main estimation results.

With regard to lender type, in line with our first hypothesis (H1), the results provide evidence that guaranteed loans issued by challenger banks and other lenders have a higher hazard of default. In economic terms, all else being equal, the hazard of default is higher by 91 %[3] and 87 % for challenger banks and other lenders, respectively, when compared to banks (Model 3, Table 3). The results confirm that due to government financial support, established lenders had the opportunity to shift the riskier portions of their loan portfolios into loan guarantee schemes, while new entrants could expand their client bases by accepting a higher default rate without loss.

Next, with respect to investor type, we found that being funded by ECF is associated with a 63 % higher hazard of default when compared to other investor types. This confirms our second hypothesis (H2), suggesting a higher riskiness of companies funded by investors not actively engaging with their investees. This result may be explained by the fact that these firms have dispersed and less active investors, and/or may be of lower quality (adverse selection) than other equity-funded firms. On the other hand, a guaranteed government loan through a 'liquidity certification effect' could help companies funded by ECF obtain additional equity investments (see Kazembalaghi et al., 2024). For the remaining investor types included in the analysis, we did not find evidence of a significantly different impact on the hazard of loan default.

In terms of the COVID loan scheme, the results show that BBLS loans are associated with an increased hazard of default by 73 % compared to other schemes. This may be because BBLS loans were relatively cheap and easily accessible, potentially influencing the behaviour of loan recipients and creating moral hazard. Borrowers had incentives to use the funds for debt refinancing, replacing higher-priced debt, rather than providing "additionality" in financial resources. This is consistent with our third hypothesis (H3).

Regarding the control variables, the results provide some evidence that companies in later stages of development experienced lower default rates, as did companies with higher liquidity or larger size.[4] Finally, companies with higher ex-ante risk scores are more likely to default on a guaranteed COVID loan which is in line with the results of Cowling et al. (2024).

In Table 4, we profile the characteristics of borrowers of each lender type. The results show that companies funded by BA are more likely to have a COVID loan from a bank. Banks and challenger banks are statistically more involved in BBLS lending compared to other schemes, while the opposite is true for other lenders. In terms of company age at loan origination date, banks and other lenders seem to prefer more stable older companies, while challenger banks attract younger ones. Further, we found that while banks were more likely to lend in 2020, challenger banks and other lenders did so in 2021. This may be because some companies were initially rejected by banks and later obtained loans from challenger banks or other lenders.

Next, banks are more likely to provide a COVID loan to firms with smaller unannounced deals, while other lenders seem to attract borrowers with larger announced deals. Financial ratios do not provide any clear signal. With respect to the ex-ante risk score, the results show that banks provide loans to less risky companies, while the opposite is true for challenger banks and other lenders. This may be because traditional banks have credit scoring systems in place, a large pool of customers, and provide loans predominantly to their clients (Cowling et al., 2024). On the other hand, challenger banks and some other lenders are new players and want to increase their client base. They may provide loans to riskier clients because they are guaranteed by the government.

To check the robustness of our findings and provide additional insights, we used alternative estimation methods. We utilised accelerating failure type (AFT) models with various distributions of errors that explicitly predict the time to failure. The results are presented in Table 5 and confirm the main results. The estimated baseline hazard functions for these models are shown in Fig. 2. The results show that for preferred models (with lower Akaike information criterion – AIC), the baseline hazard increases over time.

4. Conclusions

This study provides novel and robust evidence on the outcomes of large-scale government intervention in the form of guaranteed loans in the UK. The results show that lender and investor types are crucial determinants impacting the risk of loan default for equity-funded companies. Our findings are consistent with the hypothesis that challenger banks and other lenders are associated with higher default risk. Additionally, we find evidence for our second hypothesis in that being funded by passive investors seems to increase the default rate. Finally, generous schemes such as BBLS with full coverage, low interest rates, and minimal or no credit checks are associated with higher loan default rates.

Data availability

The data that has been used is confidential.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.econlet.2024.111941.

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[1] The group of the other lenders include alternative finance, peer-to-peer platforms, asset finance, and community lenders.

[2] We focus on the most frequent investor types. Other investor types include corporate VC, accelerators, private investment vehicles, charities and not-for-profit companies, family offices, bank VC, and undisclosed investors.

[3] The economic impact is computed as (exp(0.649) – 1)*100% = 91 %.

[4] Size enters the hazard of default non-linearly, but the impact of size on default is negative for companies with total assets over £425.

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