Article:

Cowling, M, Wilson, N orcid.org/0000-0001-5250-9894, Nightingale, P et al. (1 more author) (2024) The hazards of delivering a public loan guarantee scheme: An analysis of borrower and lender characteristics. International Small Business Journal, 42 (2). 212 -245. ISSN 0266-2426

https://doi.org/10.1177/02662426231181455

The hazards of delivering a public loan guarantee scheme: An analysis of borrower and lender characteristics.

Marc Cowling (Oxford Brookes), Nick Wilson(Leeds University Business School),

Marek Kacer (Leeds University Business School),

Paul Nightingale (University of Sussex)

Key Words: Loan Guarantees; Bank Size; Default Risk; Small Business; Credit Scoring

JEL Codes: G01; G21; L52; D25

Abstract

Using data between 2009 and 2020, we provide a detailed description of the borrowers within the Enterprise Finance Guarantee (EFG) loan portfolio, analyse time to default and how it differs across lender types. For limited companies we match additional financial and non-financial data from public and proprietary databases and profile the characteristics of EFG companies within the population of limited companies. Employing hazard models we find loans granted to unincorporated businesses by the medium-sized financial institutions are associated with a much lower hazard than those provided by smaller local lending institutions and not-for-profit agencies. Moreover, we find some evidence that loans to limited companies, issued by the big UK banking groups, have a significantly lower default than those from medium-sized financial institutions. Large banks screen out high risk firms. We argue that smaller lenders are able to price the risks rejected by the larger banks, using a wider range of credit information.

1. Introduction

One of the most pervasive themes in the small business literature is the presence of capital market imperfections that act to limit the availability of finance to smaller firms (Laeven, 2003; Gelos and Werner, 2002). Stiglitz and Weiss (1981) argued that borrower quality is *ex ante* undetectable by the lending bank (termed adverse selection) this gives the firm an unfair information advantage over the lending bank about the true distribution of expected outcomes. A common thread in these theoretical models is that collateral can act as a sorting device (Besanko and Thakor, 1987; Bester, 1985; Coco, 2000). In this lending regime, only good risk borrowers will be willing to put up collateral against a loan as they feel confident that they will not default and lose their assets. This sends a positive signal to the lender. Bad borrowers are unwilling to offer collateral against borrowing as they have a higher probability of losing it.

However, not all firms have collateral to secure their lending against and/or require funding that is greater than their collateral base. This is a particular problem for smaller and younger firms (Ghosh et al., 2000; Fraser, 2009), and firms in knowledge intensive or service industry sectors with few tangible fixed assets (Lee et al., 2015). It follows that a cadre of low-risk firms with good projects are excluded from capital markets and over time provides the underpinning rationale and justification for the type of corrective public intervention in the market that we know as a loan guarantee scheme. Loan guarantee programmes have been implemented throughout the world (Klapper et al., 2006; Honaghan, 2008) to provide loan security to smaller and younger firms who would not otherwise be able to obtain debt finance through conventional lending channels (Cowling and Clay, 1995).

In parallel, there have been longer-term fundamental shifts in the structure of lending institutions, their physical and functional distance and the way they assess loan applications (Alessandrini et al., 2010). At the global level, Berger and Udell (2006) have argued that the lending technologies that have been introduced that connect borrowers and lender have changed the way banks lend to firms and consumers (see Duqi et al., 2018). At the extreme we have new on-line banks supported by significant advances in fintech (Goldstein et al., 2019). In this respect, the traditional form of banking that was built and reinforced by direct relationships that facilitated the sharing of softer information is less prevalent today and has been replaced by automated lending technologies that are best suited to processing high volumes of hard information (Sutherland, 2018). In the UK businesses registered under the companies act (limited companies) are required to file annual financial statements and director/shareholder information as public records. Combined with other public records (eg. insolvency and closure data) this facilitates the construction of credit (risk) scores that are used by lenders and creditors to gauge relative payment and default risks. However, timely data available on the smallest companies (micro-entities) and unincorporated businesses is sparse.

In a literal and psychological sense these developments have increased the functional distance between lending institutions and small businesses (Flogel, 2018; Bellucci et al., 2018). The structural shifts are likely to have disproportionately impacted on smaller informationally opaque firms who are rooted in local areas where they typically conduct their business (Alessandrini et al., 2009; Cowling and Nadeem, 2020). However, even in a concentrated financial market such as the UK, smaller lenders still persist and they often operate on a more traditional relationship banking basis and within defined geographic localities and regions. Here the functional and physical distance between lender and borrower are, in theory, small. Moreover the time period under study is characterised by a collapse in net bank lending in the post crisis period and the advent of developments in open banking. The growth of financial technology provided technological innovations for existing banks and facilitated the entry of challenger banks and alternative lenders specialising in both the SME and consumer sectors.

Credit information is widely available to lenders through credit reference agencies who can provide basic risk scores on businesses and sole traders.

The article adds to three related literatures on credit rationing, loan guarantee schemes and differences in lending behaviour and outcomes for different sizes and types of financial institutions by focusing on potential differences in default on the UK loan guarantee scheme and the specific role of different types of lending institutions in this loan process. Moreover, the article provides some important background information on the characteristics of all the businesses that have raised finance via the loan guarantee scheme in the UK. For a sizeable subsample of EFG loan recipients (limited companies) we can provide a more detailed characteristics and risk profile along with a comparison against other private companies within the limited company population.

In the UK this is particularly important given the continual expansion of approved lenders on the scheme including some of the new challenger banks and a host of small and local not-for-profit lending institutions. The general approach is to use a Cox proportional hazard function or discrete time hazard equivalents to model the full UK Enterprise Finance Guarantee administrative data set from 2009 until the Covid-19 crisis when it was displaced by three specialist Covid-19 guarantee schemes. In total the data set contains detailed information on 32,747 firm loan contracts under guarantee. We have detailed information on firm level characteristics and loan level characteristics. Default models can be estimated for the limited company subsample of loan recipients which makes up around 80% of the EFG loan portfolio for which we have more detailed information. Moreover for some estimations we restrict the sample by excluding businsesses (observations) that were granted in the period of the financial crisis (GFC) of 2009 or into the pandemic lockdown 2020 (Covid).

We find initially that guaranteed loans issued by the big global UK banking groups have a significantly lower default than medium-sized financial institutions, while loans granted by the medium-sized financial institutions a much lower default than smaller local lending institutions and not-for-profit agencies. We find the same pattern in the sector of informationally opaque unincorporated businesses and in the sector of more transparent limited companies. This evidence is consistent with the bigger financial institutions having a relative advantage in screening loan applications as a consequence of repeated interactions with millions of small businesses. However, this effect relatively weakens once we control for relevant lending characteristics, exclude the extreme crisis years of 2009 (global financial crisis) and 2020 (Covid pandemic), or control for the selection into small, medium, and large financial institutions. More specifically, the effect of a higher default risk of loans granted by smaller financial institutions appears to be driven by the sector of informationally opaque small businesses while the effect of lower risk of loans granted by large financial institutions seems to be driven by the sector of limited companies with higher transparency and a wider range of available accounting information for assessing credit worthiness. In this sector, the effect persists even after controlling for the pre-loan default risk characteristics, or the physical distance from the company to the nearest branch of the financial institution. With respect to the perceived relatively higher loan default risk for the loans granted by smaller commercial and not-for-profit community lenders, we argue that the loan default might not be the only relevant characteristic that should be taken into account when assessing the effectiveness of the loan guarantee scheme. Introducing competition into the UK banking sector and also supporting smaller local and regional loan providers by expanding their access to loan guarantee facility through being added to the approved lenders list by the government has been a positive change as it has increased the potential supply of guaranteed loans to small informationally opaque, or simply more risky businesses. There is evidence that the larger banks select the relatively lower risk applicants amongst the EFG population (and are withdrawing from this market) but the smaller lenders are able to take on (rejects) and price the risk by combining available risk data with knowledge gained from interaction and relationship building. Moreover, this development puts the government in a stronger position when Covid-19 reached the UK and there was an immediate need to issue a million plus loans to the small business sector with great speed. More broadly, our findings can support the UK government to design its post-Covid-19 era loan guarantee schemes in order to meet the future demand from credit constrained small business and also to maintain the stability of the financial system and the sustainability of guarantee schemes themselves.

The remainder of the article is structured as follows. In Section 2 we detail the history of loan guarantee schemes in the UK and discuss the precise nature of the UK Enterprise Finance Guarantee Scheme (EFG). In Section 3 we discuss the related literature on loan guarantee scheme default and lending behaviours of different types of financial institutions. We present some testable hypotheses. In Section 4 we present our data. This includes a profile of the EFG companies within the limited company population and a detailed description of the characteristics of the EFG portfolio of loans (firms and lenders). Section 5 presents our empirical methodology for hazard modelling results and Section 6 presents the results and a discussion of our main findings. We conclude in Section 7.

2. The Evolution of Loan Guarantee Schemes in the UK

The UK has had a loan guarantee scheme since 1981 when it designed and piloted its Small Firms Loan Guarantee Scheme (SFLG). In the GFC period the long-standing SFLG was replaced by the Enterprise Finance Guarantee Scheme (EFG). The EFG scheme was designed to be relevant to a much larger pool of potential borrowers which reflected the immediate problems with increased credit rationing of business lending over and above the more traditional problems of smaller and younger businesses. Perhaps the most significant changes were a very large increase in the maximum guaranteed loan from £250,000 up to £1.2m to support guaranteed lending to larger SMEs, and also a relaxation of the scheme rule that applicants had to have exhausted all potential collateral and borrowing capacity. In this respect, the only exclusion was that an individuals' own domestic residence (the primary source of collateral wealth in the UK) could not be used as security against a loan. The usage of funds has no restrictions except the financing of specific export orders.

Whilst the guarantee coverage rate remained at 75%, it was only applied to the outstanding and unrecovered debt (and security) in the event of default. In return for providing this guarantee the government charged an interest rate premium over and above that charged by the lending institution of 2% in order to share the costs of the scheme. This significantly raised the total cost of capital to guaranteed loan borrowers but at the same time increased the willingness of lending institutions to advance loans through a de-risking effect. Of course, one potential consequence of increased borrowing rates may be adverse selection and/or low take-up rates. The EFG lenders retain full control of the lending decision and undertake the credit screening and monitoring functions. This includes decisions on all the terms and conditions including the type of facility, interest rates, and recovery actions in the event of default before claiming against the government guarantee.

This effective collateral – interest rate trade-off is well established in the theoretical literature on loan contracting and allows different types of firms and borrowers to choose an incentive compatible contract. The types of collateral – interest rate pairs that borrowers choose then acts as a signal to the lending institution about the borrower quality in the presence of imperfect, and asymmetric, information and observable risk (Gale and Helliwig, 1985; Han et al., 2009). The final and very significant change to EFG compared to its SFLG predecessor was a very significant expansion in the number of financial institutions that were legally allowed to offer

EFG loans. In 2020 there were 60 approved lending institutions (compared to around 29 under SFLG) and this expanded list included many of the new UK challenger banks and also a significant number of small local lenders and not-for-profit business support agencies. This evolution in the EFG period and specifically in terms of the number and type of financial institutions allowed to issue EFG loans provides the basis for this research.

To summarise, loan guarantee schemes in the UK originated in 1981 and have been a consistent public policy instrument for the last forty years. Within the overall provision of the guarantee scheme, there has always been exceptional provision during periods of crisis (e.g the foot and mouth epidemic in agriculture in 2007, the Global Financial Crisis from September 2008 until 2011, and in the current Covid-19 crisis). The UK guarantee scheme has three parties involved including the credit constrained firm, the lending institution, and the UK government agent (the British Business Bank). It has always been a condition of the scheme that the constrained firm has to have explored all conventional debt options before it is eligible for a guaranteed loan. It cannot apply directly to the British Business Bank for a guaranteed loan. Under EFG, all parties to the loan guarantee can have cash at risk, although 20.5% of firms with guaranteed loans have no firm collateral pledged. With no firm collateral, the lending institution has a maximum of 25% of outstanding capital at risk, and the government has a maximum of 75% of outstanding capital at risk.

The EFG scheme allows for different forms of debt including new term loans, new overdrafts, revolving lines of credit, invoice finance, asset finance, and refinancing. 95.7% of total EFG guarantees are for new term loans. In total, some £4bn in guaranteed loans were issued between 2009 and early 2020. The UK government has also introduced scheme rules that include an individual lender cap and a maximum portfolio loss rate to mitigate against opportunistic behaviours (Coco and Ferri, 2010; Rossi and Malavasi, 2016). This annual portfolio claim limit caps guarantee claims at a maximum of 20% gross (15% net) of annual lending. Lenders are also required to undergo periodic audit, in which samples of transactions are analysed to check that scheme eligibility rules and processes have been followed.

New potential EFG lenders went through a four-stage process to get accreditation including: Expression of Interest: a short submission outlining in brief how the applicant meets the requirements for lenders participating in the EFG programme. Formal Proposal: a detailed submission, providing detailed information on the applicant's organisation and its intended use of EFG. Due Diligence and Accreditation Award (subject to satisfaction of conditions precedent): due diligence will look at the applicant's business, governance, risk management and compliance frameworks. If requirements are satisfied, the lender will be offered accreditation in principle, subject to fulfilling a number of further conditions. Completion: The lender needs to sign the EFG legal agreement and have satisfied conditions precedent, including training staff and audit checks. Lenders also need to state which type or types of EFG lending they would like to become accredited for: term lending, asset finance, overdrafts or invoice finance. The formal proposal form and due diligence process will vary to take account of these different types of finance. Lenders already accredited for at least one type can approach British Business Bank informally if they would like to apply EFG to additional types of lending.

Given the due diligence process for new lenders to be accredited to issue EFG loans, it is apposite to consider the composition of types of lender, and in particular, the new entrants during the EFG guarantee period compared to the original scheme, the SFLG. The EFG included many small lending institutions with perhaps a narrower spatial focus, and not-for-profit local and regional economic development agencies. Importantly, challenger banks and peer to peer lenders entered and evolved in the lending arena, throughout this time period. Many challenger banks aimed to bring 'personal services' back to banking. Aldermore Bank describes itself as "*an SME-focused bank which operates with modern, scalable, and legacy-free infrastructure*" (Lu, 2017). According to Lu (2017) total lending of challenger banks in the UK increased by 31.5%, by volume, compared with a decline of 4.9% for the big 5 lenders by 2015. Challenger banks, such as Shawbrook, targeted the 'rationed' SME sector which had been particularly affected by the collapse in bank lending after the GFC. The aim was to help SMEs with finance for working capital, and growth. These new entrants, however, are on a mission to grow their client-base and attract borrowers that were being overlooked by larger lenders.

The information on lending in the EFG scheme by lender types is summarised in Figure 1 which tracks the number of loans advanced by each lender type over the years of EFG to 2020. It is quite clear that the larger banks have been withdrawing from lending in this scheme. Perhaps because of an inability to assess and price the risk of these borrowers from their automated systems. The lending has been taken on by the medium sized and smaller lenders, particularly in more recent years. Moreover, community lenders have played a greater role in advancing loans to EFG applicants. The medium and smaller lenders, perhaps by combining risk scores and relationship (softer information) data, are confident that they can more accurately gauge and manage default risk.

[INSERT FIGURE 1 ABOUT HERE]

3. Related Literature

In this section we consider the body of research on loan guarantee schemes and focus specifically on studies that consider default and the lending behaviours of different types of financial institutions. This latter body of research is of particular interest to our study as we will question whether there is evidence that particular types of lending institutions are better (or worse) at supporting guaranteed lending to credit rationed small business.

3.1 Loan Guarantee Schemes and Default

In terms of why loan guarantee schemes have become the most widespread form of intervention in capital markets relevant to smaller firms across the world (Beck et al., 2010; Dvouletý et al., 2021), we can identify perennial concerns that capital markets do not offer enough funds to smaller and younger firms with good quality projects (Demoussis et al., 2017; Cowling, 2010a, 2010b), and that this credit rationing negatively impacts on their ability to generate jobs, grow their sales (Dvouletý et al., 2019), introduce new products and services, increase consumer welfare through competition, and to become more productive (Kersten et al., 2017; Cowling et al., 2018a). In crisis periods, their relevance and scale are extended as banks raise their lending standards (their threshold above which a loan is approved) and ration credit more widely (Beyhaghi et al., 2020).

However, it is primarily an empirical question whether or not public loan guarantee schemes generate a positive net benefit to the host economy. In a narrow sense they expand the supply of capital to firms that would not have been able to secure the funds they need. It follows that firms that received a loan guarantee are now unconstrained and are thus able to pursue their projects and generate the positive expected outcomes they predicted. However, if default and loss rates were high (e.g. adverse selection), then this would imply that lenders were correct in their first assessment that the loan was risky and would only be issued under collateral (e.g. a charge on assets). Further, it is also the case that given the heterogeneity of small firms and indeed lending institutions then it may well be the case that loan guarantee schemes work for some firms (and lenders) but not others.

In a UK paper covering the guarantee scheme between 2000 and 2005, Cowling et al. (2018b) established that the overall guaranteed loan default rate was 28%, but behind that certain types of loans, firms, lending institutions and economic circumstances generated different outcomes.

Their study found that loans issued for working capital and to high-tech firms had significantly higher default rates but there was a negative firm size – default relationship. It was also the case that guaranteed loans issued by the big four UK multinational banks had higher default rates on average as did loans issued under guarantee in periods of economic crisis. A core analysis of default on the Canadian SBLA scheme over the period 1989-1995 found that the overall default rate was low at 6.19% and that larger sized loans defaulted more. Of particular interest was that a higher government guarantee rate was associated with an increase in default across all size classes of loan (Riding and Haines, 2001).

The two papers that are closest to this study in terms of focus and methodology are studies of the respective US SBA 7(a) loan guarantee programme by Glennon and Nigro (2005a) and the Italian Central Guarantee Fund by Caselli et al. (2021). The US study uses SBA data for the period 1983-1998 and reports an overall default rate of 16.68% with a distinct time pattern from loan origination with a peak default hazard at two years. The authors consider how default varies across lender types using the unique aspects of the programme which has a Certified Lenders Programme (CLP) from which a select group of elite lenders are re-classified onto the Preferred Lender Programme (PLP). The alternative provision is from non-bank lenders. Their results show that bank lenders had significantly lower default than non-bank lenders and that PLP and CLP lenders had lower default with PLP lenders reporting superior outcomes. Other key findings were that firm size was positively associated with default and new firms had a 9.7% higher default rate. Their final key result was that higher guarantee coverage rates were associated with higher default suggesting that lenders would only issue loans to high risk firms if the guarantee level was high enough to compensate for the additional lending risk.

An Italian study covered the period 2007-2009. They report extremely low default rates of 1.41% although the window was quite short. However, given that the time series evolution of default from origination often peaks around two years after issue, it is likely that this low default rate would be maintained over the life-course of guaranteed loans. The authors exploit the fact that two pathways to a guaranteed loan are available. One is through a direct guarantee for a loan issued by a bank and the other is through a counter guarantee from a Mutual Guarantee Institution (MGI). The core findings from hazards analysis were that micro firms have higher default, and that more profitable firms and those with a superior credit rating have lower default. Larger sized loans were also associated with higher default rates. But the key findings were that in general MGIs were more effective in terms of selecting and screening guaranteed loans apart from those issued to manufacturing firms where banks had a comparative advantage due to the availability of hard data. They interpret these findings as suggesting that MGIs are a good substitute for relationship banking which is an issue that was previously identified by Bartoli et al. (2013) in the Italian MGI context and was in part attributed to peer monitoring.

3.2 *Lending Behaviour of Different Types of Financial Institutions*

The general problem all lenders face when lending to smaller and younger businesses is their information opaqueness (Craig et al., 2005; Nguyen and Barth, 2020). It is hard financial information and 'big data' that lends' itself to sophisticated credit scoring systems that characterise large corporate banking groups and enable them to process huge volumes of standard loan applications in a quick and cost efficient manner (Gilbert and Wheelock, 2013). Moreover, scoring systems facilitate risk-based pricing so that rather than rejecting riskier applicants the lender can set an appropriate compensating price (interest rate). The ability to assess and manage risk accurately is particularly important for new entrants in the lending market. This enables them to build client bases of businesses rejected by traditional lenders, by capturing information from relationship interaction, and calibrate and compensate for the additional risk.

In contrast, the ability to transfer key soft information is facilitated through the building of lending relationships which is a more common approach adopted by smaller banks and lending institutions (Chen et al., 2015). In the UK, the merger and consolidation waves in the banking sector since the 1960s has accelerated a shift away from relational banking towards transactional lending until the reversal stimulated by UK government promotion and support for challenger banks and regional lending institutions in the last decade (Worthington, 2014; Molyneux, 2016). Credit scoring modelling and risk rating, facilitated by credit reference agency pooled lending data, have developed rapidly in consumer lending, automating and centralising the lending process. This, in part, led to a wide spread closure of the local bank branches of the large banks that impacted on traditional small business relationship lending in favour of the market based risk scoring approach. In the pre crisis period, Toms et al. argue, "business lending witnessed little automation of decision-making because of its relative complexity and the lack of available data on the (private) company sector to develop and feed risk grading algorithms. Yet banks reduced the number of (business) lending specialists at local level as part of re-engineering of processes and rationalisation of branch management. Indeed "expertise" embedded in the banking system was rapidly being replaced by bureaucratic processes, systems, and algorithms, exacerbating informational asymmetries in the entrepreneurial and smaller firm sectors" (Toms et al., 2019: 116). At the extremes it is evident that transactional banks rely largely on hard data and the remaining small, particularly local, banks and lending institutions, on soft information (relationships) to inform their lending decisions.

We have a third class of lending institution that is not a large corporate lending group, nor is it a small bank or not-for-profit. We posit that this medium-sized lending institution may have an advantage over the large transactional lenders and the small exclusively relational lenders as it brings both types of information to bear in its loan decision-making processes[1]. With this clear separation between lender types, we propose the following hypothesis:

> *H1: Middle-tier lending institutions will have an informational advantage and lower default rate on their guaranteed loans than both small exclusively relational lenders and large, transactional banks*

As the fundamental rationale for loan guarantee schemes is to support the provision of lending to credit constrained firms, it follows that the use of guarantee schemes would benefit informationally opaque and hence more likely to be credit rationed, particularly in periods of economic crisis (Cole et al., 2004; Cowling et al., 2012). These firms are likely have relatively low *tangible assets-bases* on balance sheets. Yet large transactional lending banks are not well suited to dealing with these types of businesses who often lack the volume of hard data that is required for sophisticated internal credit scoring. This suggests that smaller financial institutions who are capable of building personal relationships with firms and also accessing softer local market information will have a relative advantage in screening loan applications to informationally opaque firms. However, there is an important addition to this general observation outlined by Alessandrini et al. (2009: 261) who state that, "is not only the availability of effective information technologies or the possibility of personal face-to-face contacts with borrowers by dislocating branches in the same borrowers' area, but also the organisational complexity of the institution to which the loan office belongs. Put differently, following this line of reasoning, the local branch of a large, nationwide bank competes and allocates resources differently from the branch of a small, local bank." This gives us a second testable hypothesis:

[1] To provide context, one of the newer EFG accredited not-for-profits is a regional investment trust. Between 2018 and 2020 the trust issued 40 EFG loans with a total value of £1.6m. This compares to one of the large big-4 UK banking groups which issued 5,968 EFG loans between 2009 and 2020 with a total value of £572m. In the middle tier a typical example would be regional institution who issued 553 EFG loans between 2010 and 2020 with a total loan value of £30.5m

H2: Smaller financial institutions capable of building personal relationships with firms and also accessing softer local market information will have a relative advantage in screening loan applications to informationally opaque firms. Hence, we expect a lower hazard rate for loans issued by smaller banks for these companies.

The big banks have a lot of experience with the high-volume transactional lending and developed in-house sophisticated credit-scoring methods. We conjecture that they will be able to utilize this comparative advantage in the sector of loan guarantee lending, as well. This may manifest itself in two ways: firstly, the large lenders will be able to screen applicants more efficiently and select those with lower pre-loan risk score. Secondly, the risk associated with the loans issued by the large lenders will be lower when compared to other types of lenders, especially in the sector where more information about borrowers is available, ie.e the sector of limited companies. This leads us to the formulation of the third testable hypothesis:

H3: *Large banks screen loan applicants with established scoring models and are able to select the relatively lower risk applicants in the EFG portfolio.*

4. Data and Descriptive Statistics

The data available for this research is from the Management Information System for the EFG scheme. This is the detailed records that a lending institution has to submit to the UK government managing agency, the British Business Bank, for each loan issued under guarantee. It is the complete population of individual loan records covering the period 2009 to 2020 quarter 3 although the EFG was replaced by the Covid-19 special guarantee schemes in quarter 2 of 2020 when the pandemic arrived in the UK. In total this amounts to 32,747 individual EFG loans and we observe loan repayment or default until 2020 quarter 3. As the maximum EFG loan terms is 10 years, with an average term length of 6 years, many of the early loans have run their full term, or ended in default. As the EFG began its life within the GFC period we also account for the uniqueness of guaranteed lending at this time. For each individual loan contract the data contains the following information: *Firm characteristics* – age, size, industry sector, geographic region; *Loan contract* – date of guarantee loan origination, loan amount, loan term, loan interest rate, date loan was fully repaid or ended in default, whether firm offered collateral and if so the type of collateral, loan purpose, specific type of finance under guarantee, fixed or variable interest rate, and lending institutions.

As the EFG covered both the GFC and early Covid-19 crisis periods we augment the data set with a GFC dummy coded 1 in 2009 and 0 for all subsequent years, and a Covid-19 dummy coded 1 in 2020 and 0 for all earlier year. We create a lending institution type variable which codes small local and not-for-profit lenders as 0, medium-sized independent banks and financial institutions as 1, and the big four UK banking groups (Barclays, HSBC, Lloyds, and NatWest) as 2. In terms of the relative shares of total guaranteed loans issued Small lenders account for 4.83%, Medium-sized lenders account for a 16.16% share, and Big-banking groups account for 79.01%. A further lending institution type variable is constructed which codes not-for-profit community lenders as a distinct group coded as 1 and all commercial lenders as 0. This is designed to explicitly test whether the profit or non-profit motive leads to different lending and lending outcomes. This community lending group accounts for 2.61% of loans issued.

Moreover, for a subset of limited companies we have two important variables, distance from lender and risk score[2]. The distance from the lender allows to control for the physical distance between the borrower and the lender and was computed as a straight line ("as the crow flies") distance from the the obligor company to the nearest lender's branch[3]. Moreover, the risk score allows us to control for the pre-exising financial condition of a company (before the loan was granted) and was computed using an extended panel of the UK corporate data. For each

[2] We are grateful to the anonymous referee for suggestion to include these variables.
[3] The EFG dataset does not contain the individual addresses of lenders' branches. These were obtained partially from our panel dataset and partially using Google search. One limitation of this strategy may be that the location of a branches may change in time. Another limitation is the fact that the loan was not necessarily provided by the nearest branch.

company in the panel a risk score was computed[4]. The details of the models used to compute the risk scores are in the appendix.

4.1 *Profile of loan recipients within the private company population.*

The Management Information System for the EFG scheme provides a rich set of characteristic and loan performance variables for the loan recipients. However, within the EFG loan population, we can identify the firms that are registered under the Companies Act as limited companies and are required to file financial statements and annual returns to the central repository (Companies House). The authors have access to a data panel covering the population of limited companies over the period 1998-2022 with some 48 million company-year observations of financial (financial statements) and non-financial data (age, sector, technology, location, insolvency and other filings required by the Companies Act). In addition, each company-year has an insolvency risk probability score (Appendix, Table A1). A significant proportion of the EFG population are limited companies which facilitates: 1) the merging of a wide range of additional variables to this sub-population 2) profiling the EFG firms within the limited company population of private firms i.e. non-EFG firms.

We are able to identify 25,234 EFG loans made to limited companies and a range of other variables including the insolvency risk probability score in the year prior to the loan being granted. As an descriptive analysis we match the EFG Companies to the company population panel and profile some basic characteristics of the Loan recipients compared to the population of limited companies. Selecting the years 2008-2020 and private firms of similar characteristics to the EFG sample we have some 25 million company-year observations of private limited companies in the panel. In Table A2 we present the results of a logit regression, where the dependent variable is EFG loan (1=EFG Loan, 0=other companies). In order to profile EFG

[4] The scoring models are based on those used by credit reference agencies

firms at the time of the loan other firm-year observations of the EFG subsample are excluded from the analysis. This analysis thus provides a basic profile of the characteristics of loan recipients compared to other private firms. The models control for company age, size, sector, technology, industry sector, region and location (ONS output area classification). Additionally we flagged firms that have had a change in directors or shareholders in the previous year and a creditor charge on assets (i.e. previous collateralised borrowing). We control for economic conditions, real interest rates, GDP growth, growth in bank lending and the financial crisis (GFC dummy=1 for year 2009). Of particular interest is the ex-ante risk score (probability of insolvency). Firms applying for and being granted an EFG loan are more likely in the younger age groups (<=3years) and small company based on assets and are less liklley to be knowledge intensive firms. The GFC has a positive and significant sign indicating that this period involved a relatively larger number of loans. The EFG firms are more likely to be located in urban and metropolitan areas. The charge on asset dummy is positive and significant that may imply that the firm has already collateralised borrowing. The company risk score is of particular interest and is highy significant and positive. This indicates that the EFG firms would be deemed a higher insolvency risk than comparable private companies. We provide further detailed descriptive statistics of the EFG sample and subsamples in the next section.

4.2 Detailed descriptive statistics and sub-populations

Details of the EFG loan portfolio has not been available for academic research so we provide a detailed description of the loan and borower characteristics over the time period. For this analysis we exclude loans (borrowers) where the loan guarantee was cancelled at some stage. There are 2,583 cancelled loans reducing the sample from 32,747 to 30,164. Table 1.1 splits the sample data into our three lender types for the whole sample and Table 1.2 presents the key variables for analysis by two borrower types (incorporated and unincorporated businesses). On firm demographics, in Table 1.1 we find that small lenders issue loans to firms with smaller annual sales (median £282,856), employment (median 3.82), and also to younger firms (median 3.0). However, we also note that medium-sized lenders issue loans to firms with the largest annual sales (median £706,406) and employment (median 5.92), but at a slightly younger stage in their life than large lenders. The findings regarding small lenders is consistent with a focus on processing softer information from the most informationally opaque firms. There were differences between lender types in terms of the respective industry sector distributions too. Small lenders had an over-representation in agriculture, information & communications, and professional & scientific services, the latter two being examples of knowledge based service industries. Medium-sized lenders had an over-representation in transport industries, and large lenders an under-representation in manufacturing and administrative support services, and an over-representation in wholesale & retail, hotels & catering, and health care services. Geography is important and we find that large lenders have a higher concentration of their guaranteed lending in London (the capital city and financial centre) and the South East (the region that surrounds London) which are the wealthiest regions of the UK and the most densely populated. The London and South East share for large lenders is 29.44% and this compares to only 12.47% for medium-sized lenders and only 10.24% for small lenders. These regional findings can help explain why medium-sized lenders are able to capture quite large small firms that may be under-served by the big four banking groups in other regions of the UK.

[INSERT TABLE 1.1 ABOUT HERE]

In respect of loan contract features, we find that small lenders issue the smallest loans (median £32,346) and larger lenders the largest loans (median £80,892). The median loan maturity is 60 months across all lender types. There are differences in the loan interest rate offered and the median rate is diminishing in size of lender from 12% for small lenders, to 6.79% for medium-sized lenders, to 4.75% for large lenders. The use of fixed rate loan interest rates, which is associated with contractually insuring borrowers against future adverse economic circumstance, is nearly four times higher for small lenders than large lenders. The offer of loans with no firm collateral is most common in loans issued by small lenders and lowest in large lenders. Taken together, these results suggest that large lenders are most happy making secured loans at low interest rates to larger borrowers, even on a loan guarantee scheme.

There are some interesting differences in respect of the purpose of the guaranteed loan. Here we find that small lenders make a higher share of loans for asset finance, capital investment, and to start-ups. Medium-sized lenders offer 58% of guaranteed loans for working capital. In contrast, large lenders issue loans for firm growth with 47% of total loans for this purpose. In this respect small lenders focus on promoting new firms and young firms investing in capacity building, whereas medium-sized lenders focus more on liquidity for day-to-day operational purposes. Large lenders offer loans to more mature firms looking to enter a growth phase of their life-cycle.

On loan default we note that small lenders had the highest overall default rate at 29% which compares to 24% for medium lenders and 26% for large lenders. For defaulting loans, the timing is also different from the point of loan origination. Here we find that average defaults with small lenders occurred at approximately 22 months (663 days) after issue. This compares to over 22.5 months (671 days) for medium-sized lenders and nearly 30 months (890 days) for large lenders. In its totality this higher (lower) default and earlier (later) time to default at small (large) lenders must be balanced against the higher (lower) interest rate and the respective differences in firm collateral.

[INSERT TABLE 1.2 ABOUT HERE]

Tables 1.2 and 1.3 provide subsample descriptive statistics for two distinct subsamples of the EFG loan portfolio, limited companies and unincorporated businesses and default versus non-default. Private limited companies comprise 80.8% of the sample. The tables include the results of statistical tests of differences between the groupings. Table 1.2 shows significant differences between the borrower types across a wide range of loan and borrower characteristics, although default rates are not significantly different (c 25%). In terms of lender type, medium lenders have a bigger proportion of their loans with limited companies. Unincorporated businesses are smaller in terms of turnover whereas 34% of limited companies have a turnover greater than £1.2m. The limited companies have a larger average loan size (£133,000) but shorter loan terms (68.6 months). They also borrow at a slightly lower interest rate (5.94 versus 6.14). The limited companies are more likely to use the loan for working capital reasons whereas unincorporated businesses are citing growth, predominantly. There is very little difference in regional or industry distribution.

[INSERT TABLE 1.3 ABOUT HERE]

Table 1.3 analyses differences in the subsamples of defaulted versus non-defaulted loans. Generally, the smaller and younger business have a higher default rate with an average loan size of defaulted businesses is nearly £100,000. These businesses pay a higher interest rate (6.9% versus 5.7%) and defaults have a higher incidence in the 'working capital' purpose category. There is little difference in relation to collateral but a higher incidence of default in loans given in 2009. The pattern of default is similar within the two subsamples of limited and unincorporated business.

5. Empirical Methodology

We estimate a Cox's proportional hazards models, determining default, using a rich set of firm and loan contract variables described above (see also Caselli et al., 2021 and Glennon and Nigro, 2005a, 2005b). The model allows us to estimate the hazard risk of a loan defaulting as a function of firm demographics and loan contract parameters. The dependent variable is specified such that the individual loan time begins at its origination date and continues until its default date when it ends. For loans that have not defaulted by the end of the sample period (quarter 3 of 2020) the data are censored at this point.

The hazard function is h(t) and is the risk of default at time t which is the survival time. It follows that h(t) is the hazard function which is determined by a set of several covariates (vectors LT_i, FD_i, LC_i, IT_i, TFE_i, and AFI_i) and the respective vectors of coefficients α_k (k = 1, 2, … , 6) which measure the effect of this set of covariates on hazard rate. Subscript *i* represents each individual firm loan contract, and *t* represents time.

$$h(t) = h_0(t)\exp\left(LT_i^T\alpha_1 + FD_i^T\alpha_2 + LC_i^T\alpha_3 + TFE_i^T\alpha_4 + IT_i^T\alpha_5 + AFI_i^T\alpha_6\right) \qquad (1)$$

A key vector of variables for us given our interest in small, medium, and large financial intermediaries is the LT_i which represents the indicators of lender type issuing the guaranteed loan. As we have three types of lender, the components of the vector LT_i are the indicators of small and large lenders, while the medium lender is the reference category. The vector FD_i represents our firm demographics at the time of loan origination (size, age, industry sector, and geographical region) which have all been found to be important in the determination of firm survival and loan default. The vector LC_i represents loan contract variables (loan term, loan amount, interest rate, loan purpose, collateral). Vector TFE_i captures fixed time effects. The vector IT_i contains our lender type and unincorporated subsample interaction terms to allow us to test whether the impact of lenders differs in subsamples of the unincorporated, and limited companies. Finally, vector AFI_i represents the vector of additional firm information before the loan available for a subset of limited companies.

Following Caselli et al (2021) a Heckman selection approach is employed to address the potential for selection bias using a two-stage estimation procedure and a binary outcome model for selection into lender typer. The inverse Mills ratio (IMR) is then entered in the survival model at the second stage (see Lennox et al., 2012). All models were re-estimated using discrete time hazard techniques using panel logit regression for robustness checking (not reported but available from the authors).

6. Modelling Default Hazard

6.1 Results for Small, Medium, and Large Lenders

In this section, utilising the full sample, we move on to our formal estimation of default hazard. We begin by plotting the basic survival function for the portfolio of guaranteed loans issued by each of our three lender types with no covariates. This is shown in Figure 2 Panel A below and shows that at any point in time from loan origination small lender guaranteed loans are associated with a lower survival rate and around 66 months there is a clear deterioration in relative survival for small lender issued loans. In contrast, medium-sized and large lenders have very similar survival rates across time. For the government who provides the guarantee coverage, the probability that the guarantee will be called upon is higher for small lenders.

[INSERT FIGURE 2 ABOUT HERE

Figure 2 Panel B shows that the pattern of survival and default over time from the point of loan issue is similar between commercial and community banks, although in the early phase of loan term community bank loans have a slightly higher default rate. For loans surviving into their seventh year it is also apparent that community bank loans have a marginally lower default rate from that point onwards until the maximum term of ten years. Further descriptive analysis reveals some interesting differences in firm characteristics and loan contracting. Community banks advance EFG loans to younger firms but those with larger employment on average. They make loans of longer maturity which implies that they are more patient lenders but of smaller scale. In this sense the types of loans they issue under guarantee to younger firms allow them the greatest opportunity to service them as the per period capital and interest rate payments are lower thus requiring the firm to generate less free cash to meet the loan repayment schedule.

Table 2 reports our baseline models. The hazard of default is the dependent variable of interest. We provide estimates for the whole sample (N = 30,174) and the unicorporated and limited company sub-populations. For the whole sample, in model 1, besides our main variables of interest – indicators of lender type – we include core firm demographics – the indicator of unincorporated business, real turnover, age, geographic region, industry sector and time fixed effects. Model 2 is augmented to include key loan contract variables such as loan term, loan size, interest rate, loan purpose, indicator of fixed interest rate, and a dummy variable if the firm placed no collateral. Model 3 adds two interaction terms to test for differences in lender type and business type. The reported coefficients are hazard rates. The colums 4 and 5 repeat this specification for the unincorporated businesses and columns 6-10 provide specifications for limited companies. For the limited company sub-population we add additional variables. First the calculated distance from borrower to the nearest branch of the lender and a wide range of firm financial and non-financial characteristics. This includes the calculated insolvency risk score (pre loan) and firm level characteristics. We also control for industry competition and industry risk (prior failures). Table 3 repeats the estimation but excluding the years 2009 (GFC) and 2020 (Covid) , as a robustness test.

In general, we find that the relationship between lender types and default does vary and change as we build models with a richer set of variables. In our full sample model we find a negative relationship between lender size and default. By adding in loan characteristics and our lender type – firm characteristic interaction terms small lenders have a higher default with unincorporated business.

[INSERT TABLE 2 ABOUT HERE]

In relation to hypothesis 1 we expect that the medium-sized lenders achieve superior performance attributable to their use of both the sophisticated scoring models adopted by the large lenders and the soft (relationship) information coming from their closer interaction with the companies. This hypothesis is tested using the indicators of small and large lenders as the test variables. Since the reference category is the medium lender, the coefficients for the small and large lenders quantify differences with respect to the reference category of medium-sized lenders. Hence, if the exponentiated estimated coefficients are greater than unity and are statistically significant, this would mean that all else equal, the loans granted by the small and large lenders have higher hazard of failure than the loans granted by the medium lenders. Moreover, in the subsample of the informationally opaque (unincorporated) businesses, the medium lenders should have a clear advantage over the large lenders because they should be able to use the soft information. Similarly, in the sample of limited companies, the medium-sized lenders should have advantage over the small lenders because of their sophisticated large volume credit scoring models.

With respect to the hypothesis 2, we expect the coefficient for small lenders to be lower than unity in the sample of informationally opaque unincorporated companies, signifying that the hazard associated with the loans provided by the small lenders is lower compared to medium lenders. This is because small lenders are expected to have developed expertise to process soft information due to a closer relationship with the borrower, especially when hard information is scarce.

Finally, the hypothesis 3 assumes the existence of superior screening abilities of the large banks, especially in the environment where hard information, such as accounting information, is readily available. If this is so, in a sample of private limited companies, we expect the coefficient for the large lenders to be lower than unity, suggesting a lower hazard for the loans granted by the large lenders. Moreover, we expect the large lenders to be able to select borrowers with a lower default risk prior to providing the loan.

Initially, we use models (1), (4) and (6) in Table 2 to test our hypotheses. In model (1), the exponentiated estimated coefficient for the indicator of the small lenders is greater than unity and it is statistically significant. This seems to suggest that loans granted by the smaller local lending institutions and not-for-profit agencies have higher hazard of failure when compared to those provided by medium-sized financial institutions. On the other hand, the exponentiated coefficient for the large lender is lower than unity and it is statistically significant, as well, suggesting that loans issued by the big global UK banking groups have a significantly lower default than medium-sized financial institutions. This seems to confirm hypothesis 1. Inteerestingly, the same situation is in the sector of informationally opaque unincorporated businesses (model (4)), which would lead to rejection of thypothesis 2 since it seems that the loans from small lenders have higher hazard of default. Moreover, the results are the same in the sector of more transparent limited companies (model (6)), as well, which preliminary confirms hypothesis 3.

Next, we use the results of models (2), (5) and (7) with comprehensive set of the control variables (at least with respect to the available data) to test our hypotheses. The coefficients of the indicators of both small and large lenders in the model (2) are greater than unity which suggests that the hazard of loans granted by the small and large lenders are greater, however, these figures are not statistically different from unity, so all else equal, in the sample comprising both types of companies the loans granted by different types of lenders are similarly risky. So this would be evidence against hypothesis 1. In model (5) we expect the coefficient of the indicator of the large lender to be significantly greater than unity signifying that the medium lenders are better positioned to utilize the soft information about the informationally opaque unincorporated companies. The coefficient is indeed greater than unity but it is not statistically significant. On the other hand, the coefficient for the indicator of the small lenders is greater than unity and statistically significant, so all else equal, the loans granted by the small lenders are riskier than those granted by the medium lenders which is contrary to initial expectations[5]. This is evidence against hypothesis 2. Finally in model (7) the exponentiated coefficients of interest are not significant, so loans of all types of lenders are equally risky – evidence against hypothesis 3[6]. Or they form a heterogenous group of fintech banks with traditional ones and the results cancel out. The same situation is in models (8), (9) and (10) where we include in various combinations the distance between the borrowing company and the nearest branch of the lender, pre-loan risk score, and a wide range of other variables controlling for the financial and non-financial characteristics.

[INSERT TABLE 3 ABOUT HERE]

In table 3, we undertake some robustness checking. After restricting the sample to the period without the crises years of 2009 and 2020, the results of testing the hypotheses 1 and 2 remain very similar to those obtained before when the unrestricted sample was employed. In models (1), (4) and (6) the results seem to suggest that the guaranteed loans issued by the big global UK banking groups have a significantly lower default than medium-sized financial institutions, while loans granted by the medium-sized financial institutions a much lower default than smaller local lending institutions and not-for-profit agencies. Similar to Table 3, in model (2), the coefficients of the small and large lenders' indicators remain statistically insignificant which means there was no significant difference between the hazard of loans granted by different types of lenders once we control for relevant variables. Looking at model (5) estimated using the sample of unincorporated companies, the size of the coefficients for the indicators of small and large lenders are similar to those in Table 2, too, the only difference is

[5] It may be that the worse performance of the small lenders in the subsample of the unincorporated companies is driven by not-for-profit community lenders. The not-for-profit community lenders are not motivated by achieving profits but serving their community.

[6] These results may even suggest that the medium lenders are similar to the large ones and do not exist as a specific group.

that the statistical significance of the coefficient for the small lender decreased somewhat – in Table 2 it was statistically significant at the level of 5% now it is statistically significant at the level of 10%. In the sample of limited companies, the coefficient for the large lender is statistically significant at the level of 10% (models (7) and (8)) and its exponentiated value is below unity. This suggests that in the sample of more transparent companies with rich set of available accounting information, all else equal, the loans granted by the large lenders are somewhat less risky than those granted by the medium lenders. Conversely, this means that the scoring methods of the large lenders may be superior to those of the medium lenders in this time period and/or the larger lenders are cherry picking the lower risk firms. Of course, the challenger banks are relatively new and still gaining expertise and experience. Moreover they may be focussed on increasing their client base and the EFG scheme provides and way of achieving this at lower overall risk. Nevertheless, this provides some evidence in favour of our hypothesis 3.

6.2. *Models profiling lender type*

For each lender type we estimate models determining lender probability as an additional descriptive analysis. The results are reported in Table 4 that show the estimation results for these selection models[7]. The Unincorporated (Limited Company) subsample includes companies without (with) company registered number. The estimates are used in the calculation of inverse Mills ratio and hazard models that control for selection. The final Cox's hazard model specifications are reported later in Table 5.

[INSERT TABLE 4 ABOUT HERE]

[7] With respect to the identification strategy, Lennox et al. (2012) stress that besides non-linearities (which we introduced besides the functional form of probit also by using polynomials), we use one indicator of loan purpose „Other" which is not associated with default at the 5% significane level – see Table 1.3 for details.

The selection equations control for pre loan risk score in the company sub-population, compamy size (employment), age, loan term and purpose and time dummies. Of particular interest is the coefficient on risk score models 7-9. It is clear that large lenders select loan applicants with relatively lower insolvency risk scores and longer loan terms whereas the smaller lenders take on the relatively higher risks with shorter terms. Relating to unincorporated business the larger lenders advance loans to the older businesses and again over longer terms. Since in model (9) the coefficient for the risk score is negative, this means that the large lenders indeed select predominantly borrowers with lower ex ante risk score which is evidence in favour of our hypothesis 3.

[INSERT TABLE 5 ABOUT HERE]

The results presented in table 5 reveal some evidence of the self-selection bias. Firstly, in the model (2), the inverse Mills ratio is statistically significant for the large lender. This seems to suggest that there is some unobserved variable that determines both the hazard and choice of large lender. Consequently, once controlled for this bias, the hazard of large lender is significantly smaller than that of the medium lender – which goes against hypothesis 1.

Similarly, in model (5), the inverse Mills ratio for the small lender is significant, again suggesting some unobserved variable that determines both the loan default and choice of small lender. Qualitatively, the finding from Table 3 that the loans granted by small lenders are more risky remains unchanged, just the magnitude of effect increases. This is evidence against hypothesis 2. Finally, in the model (7), the inverse Mills ratio for the large lender is statistically significant, suggesting again the confounding effect of unobserved variables. When looking at the estimated coefficient for the large lender, it is statistically significant at level of 5%, suggesting that the loans from large lenders are less risky when compared to those from the medium lenders. This reinforces the evidence in favour of our hypothesis 3.

All in all, with respect to the hypothesis 1, there is some evidence that medium lenders achieve better performance when compared to the small lenders, for unincorporated businesses. At the same time, the loans granted by the medium lenders are riskier than those from the large ones, and this seems to be driven by the (relatively large) segment of limited companies. On the other hand, the hypothesis 2 is rejected since it seems that in the sector of informationally opaque unincorporated businesses loans from small lenders as a group are associated with higher hazard of failure when compared to other types of borrowers. Finally, the hypothesis 3 seems to be confirmed in our models. Firstly, the large borrowers are able to select borrowers with lower ex ante risk, and secondly, all else equal, in the limited companies sector the loans provided by large lenders are less risky.

7. Conclusions

This article provides new evidence on one of the larger loan guarantee schemes in the pre-Covid-19 world, the UK EFG. In doing so it complements and extends a small but growing body of international work on this issue. The article is the first to provide detailed descriptive information on the characteristics of EFG loans, borrowers and lenders; the trends over the time period and a profile of EFG recipients compared to other private firms in the population. In addition, our approach was to model the default risk of publicly guaranteed loans issued to SMEs in the UK. The specific lens we looked through was on the intermediary lending and relatively new institutions which are now fundamental to the UK scheme. This was important as there has been a significant expansion in the number of lenders approved by the UK government to issue EFG loans and much of this pool of newly approved lenders was medium-sized banks as well as local, place-based, lenders, development agencies and not-for-profit community lending institutions. We find evidence that these lenders are providing finance to SME's and taking on the risks that the larger banks avoid.

Our work also has a more current and forward looking aspect as during the Covid-19 crisis the UK government introduced three new guarantee schemes with great haste and it was only the significant expansion in approved lenders that was able to support an exponential growth in loans issued under public guarantee from around 3,000 per annum to in excess of 1 million. With a current contingent liability totalling £80bn (including £46.5bn to small businesses) it is apposite to question what the potential implications are going forward given the diversity of the lender population. At this scale, the UK guarantee schemes could represent a risk to broader financial stability, and also to internal viability if default rates are excessive. It appears apposite to use what evidence we have on UK loan guarantee schemes to offer insight in these respects.

In terms of the viability of UK loan guarantee schemes, we suggest that the expansion in the approved lender pool, particularly to smaller local lenders, has at worst not increased their long-run sustainability, and at best might have enhanced it if in the future there is an increase in capital constrained entrepreneurs without collateral. As the huge Covid-19 UK guarantee schemes are beginning to enter their repayment terms (after a 12 month holiday), it may well be that with the 100% guarantee coverage provided smaller lenders and community lending institutions were best placed to deal with lending as firms had no skin in the game, even if they actually did have assets and the ability to provide collateral. *Ex post* assets can be recovered in default, but that was not revealed at the point of issue of the Covid-19 guaranteed loan.

Overall financial stability in the UK would not normally be an issue as the annual contingent liability to the government would be in the region of £300m. In this sense, unless default rates were seriously high and the time to default was seriously short, the UK scheme has always been very modest and unlikely to present a threat to financial stability. Now, however, all that has changed since Covid-19. The totality of guaranteed lending is huge and does present a genuine threat to financial stability going forward. Our findings, if rolled forward from EFG to the Covid-19 guarantee schemes, suggest that the potential threat to overall financial stability is perhaps less than it might be due to the diversity of the UK approved guarantee lender pool. Further, community lending institutions and small local banks play an important role in the small firm financing ecosystem.

References

Alessandrini P, Presbitero AF and Zazzaro A (2009) Banks, distances and firms' financing constraints. *Review of Finance* 13(2): 261–307.

Alessandrini P, Presbitero AF and Zazzaro A (2010) Bank size or distance: what hampers innovation adoption by SMEs? *Journal of Economic Geography* 10(6): 845–881.

Bartoli F, Ferri G, Murro P and Rotondi Z (2013) Bank–firm relations and the role of Mutual Guarantee Institutions at the peak of the crisis. *Journal of Financial Stability* 9(1): 90–104.

Beck T, Klapper LF and Mendoza JC (2010) The typology of partial credit guarantee funds around the world. *Journal of Financial Stability* 6(1): 10–25.

Bellucci A, Borisov A, Giombini G and Zazzaro A (2019) Collateralization and distance. *Journal of Banking & Finance* 100: 205–217.

Berger AN and Udell GF (2006) A more complete conceptual framework for SME finance. *Journal of Banking & Finance* 30(11): 2945–2966.

Besanko D and Thakor AV (1987) Competitive equilibrium in the credit market under asymmetric information. *Journal of Economic Theory* 42(1): 167–182.

Bester H (1985) Screening vs. rationing in credit markets with imperfect information. *The American economic review* 75(4): 850–855.

Beyhaghi M, Firoozi F, Jalilvand A and Samarbakhsh L (2020) Components of credit rationing. *Journal of Financial Stability* 50: 100762.

Caselli S, Corbetta G, Cucinelli D and Rossolini M (2021) A survival analysis of public guaranteed loans: Does financial intermediary matter? *Journal of Financial Stability* 54: 100880.

Chen Y, Huang RJ, Tsai J and Tzeng LY (2015) Soft information and small business lending. *Journal of Financial Services Research* 47(1): 115–133.

Coco G (2000) On the use of collateral. *Journal of Economic Surveys* 14(2): 191–214.

Coco G and Ferri G (2010) From shareholders to stakeholders finance: a more sustainable lending model. *International Journal of Sustainable Economy* 2(3): 352–364.

Cole RA, Goldberg LG and White LJ (2004) Cookie cutter vs. character: The micro structure of small business lending by large and small banks. *Journal of financial and quantitative analysis* 39(2): 227–251.

Cowling M and Clay N (1995) Factors influencing take-up rates on the loan guarantee scheme. *Small Business Economics* 7(2): 141–152.

Cowling M (2010a) Economic Evaluation of the Small Firms Loan Guarantee (SFLG) Scheme. Institute for Employment Studies, Department for Business Innovation and Skills, UK Government

Cowling M (2010b) The role of loan guarantee schemes in alleviating credit rationing in the UK. *Journal of Financial Stability* 6(1): 36–44.

Cowling M, Liu W and Ledger A (2012) Small business financing in the UK before and during the current financial crisis. *International Small Business Journal* 30(7): 778–800.

Cowling M, Liu W and Zhang N (2018a) Did firm age, experience, and access to finance count? SME performance after the global financial crisis. *Journal of Evolutionary Economics* 28(1): 77–100.

Cowling M, Ughetto E and Lee N (2018b) The innovation debt penalty: Cost of debt, loan default, and the effects of a public loan guarantee on high-tech firms. *Technological Forecasting and Social Change* 127: 166–176.

Cowling M and Nadeem SP (2020) Entrepreneurial firms: with whom do they compete, and where? *Review of Industrial Organization* 57(3): 559–577.

Craig BR, Jackson WE and Thomson JB (2005) The role of relationships in small-business lending. Federal Reserve Bank of Cleveland Economic Commentary (Oct 15, 2005): 1–4.

Demoussis M, Drakos K and Giannakopoulos N (2017) The impact of sovereign ratings on euro zone SMEs' credit rationing. *Journal of Economic Studies* 44(5): 745–764.

Duqi A, Tomaselli A and Torluccio G (2018) Is relationship lending still a mixed blessing? A review of advantages and disadvantages for lenders and borrowers. *Journal of Economic Surveys* 32(5): 1446–1482.

Dvouletý O, Srhoj S and Pantea S (2021) Public SME grants and firm performance in European Union: A systematic review of empirical evidence. *Small Business Economics* 57(1): 1–21.

Dvouletý O, Čadil J and Mirošník K (2019) Do firms supported by credit guarantee schemes report better financial results 2 years after the end of intervention? *The BE Journal of Economic Analysis & Policy* 19(1): 20180057.

Fraser S (2009) Is there ethnic discrimination in the UK market for small business credit? *International Small Business Journal* 27(5): 583–607.

Flögel F (2018) Distance and modern banks' lending to SMEs: ethnographic insights from a comparison of regional and large banks in Germany. *Journal of Economic Geography* 18(1): 35–57.

Gale D and Hellwig M (1985) Incentive-compatible debt contracts: The one-period problem. *The Review of Economic Studies* 52(4): 647–663.

Gelos RG and Werner AM (2002) Financial liberalization, credit constraints, and collateral: investment in the Mexican manufacturing sector. *Journal of Development Economics* 67(1): 1–27.

Gilbert RA and Wheelock DC (2013) Big banks in small places: are community banks being driven out of rural markets? *Federal Reserve Bank of St. Louis Review* 95(3): 199–218.

Glennon D and Nigro P (2005a) Measuring the default risk of small business loans: A survival analysis approach. *Journal of Money, Credit and Banking* 37(5): 923–947.

Glennon D and Nigro P (2005b) An Analysis of SBA Loan Defaults by Maturity Structure. *Journal of Financial Services Research* 28(1/2/3): 77–111.

Ghosh P, Mookherjee D and Ray D (2000) Credit rationing in developing countries: an overview of the theory. In: Mookherjee D and Ray D (eds) *A Reader in Development Economics*. Blackwell, pp.283–301.

Goldstein I, Jiang W and Karolyi GA (2019) To FinTech and beyond. *The Review of Financial Studies* 32(5): 1647–1661.

Han L, Fraser S and Storey DJ (2009) Are good or bad borrowers discouraged from applying for loans? Evidence from US small business credit markets. *Journal of Banking & Finance* 33(2): 415–424.

Honaghan P (2008) *Partial credit guarantees: Principles and practice. Session I. Partial Credit Guarantees: Experiences and Lessons.* World Bank, Financial & Private Sector Development. Washington DC.

Kersten R, Harms J, Liket K and Maas K (2017) Small Firms, large Impact? A systematic review of the SME Finance Literature. *World development* 97: 330–348.

Klapper LF, Sarria-Allende V and Zaidi R (2006) A firm-level analysis of small and medium size enterprise financing in Poland. *World Bank Policy Research Working Paper* 3984.

Laeven L (2003) Does financial liberalization reduce financing constraints? *Financial Management* 332(1): 5–34.

Lee N, Sameen H and Cowling M (2015) Access to finance for innovative SMEs since the financial crisis. *Research policy* 44(2): 370–380.

Lennox CS, Francis JR and Wang Z (2012) Selection Models in Accounting Research. *The Accounting Review* 87(2): 589–616.

Lu L (2017) Financial Technology and Challenger Banks in the UK: Gap Fillers or Real Challengers? *Journal of International Banking Law and Regulation* 32(7): 273–282.

Molyneux P (2016) Banking in the UK. In *The Palgrave Handbook of European Banking*. London: Palgrave Macmillan, pp.501–520.

Nguyen NT and Barth JR (2020) Community banks vs. non-community banks: Where is the advantage in local small business funding? *Atlantic Economic Journal* 48(2): 161–174.

Riding AL and Haines G (2001) Loan guarantees: Costs of default and benefits to small firms. *Journal of business venturing* 16(6): 595–612.

Rossi SP and Malavasi R (eds) (2016) *Financial crisis, bank behaviour and credit crunch*. Springer International Publishing.

Stiglitz JE and Weiss A (1981) Credit rationing in markets with imperfect information. *The American economic review* 71(3): 393–410.

Sutherland A (2018) Does credit reporting lead to a decline in relationship lending? Evidence from information sharing technology. *Journal of Accounting and Economics* 66(1): 123–141.

Toms S, Wilson N and Wright M (2019) Innovation, intermediation, and the nature of entrrepreurship: A historical perspective. Strategic Entrepreneurship 14(1): 105–121.

Worthington S (2014) Challenger banks: are they for real? The impact of new entrants on financial services competition. In *The Routledge Companion to Financial Services Marketin*. Routledge, pp.60–72.

Table 1.1 Descriptive statistics – lender types

		Whole sample	Small	Lender type Medium	Large	Test of differences in means for lender types
		N = 30,164	N = 1,553	N = 4,857	N = 23,754	
Annual Turnover - real (CPIH)						
	Mean	1,437,960	1,025,785	1,967,275	1,356,678	***
	Median	543,915	282,856	706,406	539,054	
	SD	2,769,616	2,283,167	3,541,155	2,600,309	
Employment						
	Mean	22.25	26.03	19.64	22.54	***
	Median	5.15	3.82	5.92	5.07	
	SD	40.12	46.05	34.64	40.72	
Age (years) at loan origination						
	Mean	8.50	6.02	8.29	8.71	***
	Median	5.00	3.00	5.00	5.00	
	SD	11.62	8.52	11.13	11.87	
Loan Amount - real (CPIH)						
	Mean	122,955	52,641	124,400	127,256	***
	Median	73,736	32,346	54,670	80,892	
	SD	152,721	83,046	186,982	147,233	
Loan term (months)						
	Mean	72.38	52.93	55.24	77.16	***
	Median	60.00	60.00	60.00	60.00	
	SD	33.16	16.64	29.41	33.08	
EFG Interest Rate						
	Mean	5.98	11.28	8.96	5.02	***
	Median	5.00	12.00	6.79	4.75	
	SD	3.52	4.64	5.48	1.91	
Loan Purpose						
	Asset Finance	0.01	0.05	0.04	0.00	***
	Capital Investment	0.06	0.11	0.06	0.06	***
	Growth	0.43	0.34	0.24	0.47	***
	Other	0.01	0.00	0.02	0.01	***
	Start-up	0.13	0.16	0.07	0.14	***
	Working Capital	0.37	0.33	0.58	0.33	***
Fixed interest rate						
	Fixed interest rate = 1	0.24	0.80	0.29	0.20	***
No collateral						

	No collateral = 1	0.32	0.64	0.48	0.27	***
Defaulted Loan						
	Defaulted Loan = 1	0.25	0.29	0.24	0.26	***
Time to fail (days)						
	Mean	844.11	662.88	671.38	890.31	***
	Median	686.00	549.50	545.00	729.00	
	SD	618.56	502.55	502.23	637.84	

Notes:

The table shows the descriptive statistics for the whole sample and the subsamples determined by the size of lender. In the last column, the test for the difference in means in the three samples is presented – the statistical significance is indicated with asterisks (*, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively).

Table 1.2 Descriptive statistics – unincorporated vs limited companies

	Whole sample N = 30,164		Unincorporated N = 5,781		Limited companies N = 24,383		Test of differences limited vs unincorp.	
	Mean	SD	Mean	SD	Mean	SD	Difference	p-value
Defaulted Loan	0.25	0.44	0.25	0.43	0.26	0.44	0.01	0.26
Small lender	0.05	0.22	0.05	0.21	0.05	0.22	0.00	0.13
Medium lender	0.16	0.37	0.09	0.28	0.18	0.38	0.09	0.00
Large lender	0.79	0.41	0.87	0.34	0.77	0.42	-0.10	0.00
Annual Turnover - real (CPIH)	1,437,960	2,769,616	463,587	1,039,207	1,668,976	2,992,496	1,205,389	0.00
Real turnover <= 200k	0.24	0.43	0.42	0.49	0.20	0.40	-0.22	0.00
Real turnover 200k - 500k	0.23	0.42	0.31	0.46	0.22	0.41	-0.09	0.00
Real turnover 500k - 1.2m	0.24	0.43	0.21	0.41	0.25	0.43	0.03	0.00
Real turnover > 1.2m	0.29	0.45	0.06	0.24	0.34	0.47	0.28	0.00
Age (years) at loan origination	8.50	11.62	11.32	15.26	7.84	10.47	-3.48	0.00
Age 0-3	0.40	0.49	0.40	0.49	0.40	0.49	0.01	0.21
Age 4-6	0.18	0.38	0.13	0.34	0.19	0.39	0.06	0.00
Age 7-10	0.16	0.37	0.12	0.33	0.17	0.37	0.05	0.00
Age > 10	0.26	0.44	0.35	0.48	0.24	0.43	-0.11	0.00
Loan Term	72.38	33.16	88.18	32.00	68.64	32.32	-19.54	0.00
Loan Amount - real (CPIH)	122,955	152,721	78,693	92,422	133,449	162,031	54,756	0.00
EFG Interest Rate	5.98	3.52	6.14	3.04	5.94	3.63	-0.20	0.00
Fixed interest rate	0.24	0.43	0.28	0.45	0.24	0.42	-0.05	0.00
Loan Purpose: Asset Finance	0.01	0.09	0.00	0.05	0.01	0.10	0.01	0.00
Loan Purpose: Working Capital	0.37	0.48	0.21	0.41	0.41	0.49	0.20	0.00
Loan Purpose: Capital Investment	0.06	0.24	0.05	0.22	0.06	0.24	0.01	0.01
Loan Purpose: Growth	0.43	0.49	0.61	0.49	0.38	0.49	-0.23	0.00
Loan Purpose: Other	0.01	0.09	0.01	0.07	0.01	0.09	0.00	0.08
Loan Purpose: Start-up	0.13	0.34	0.12	0.33	0.13	0.34	0.01	0.11
No collateral	0.32	0.47	0.60	0.49	0.26	0.44	-0.35	0.00
Year 2009 (GFC)	0.18	0.38	0.22	0.41	0.17	0.38	-0.05	0.00
Year 2010	0.15	0.36	0.20	0.40	0.14	0.35	-0.05	0.00
Year 2011	0.10	0.30	0.12	0.33	0.09	0.29	-0.03	0.00
Year 2012	0.08	0.27	0.08	0.27	0.08	0.27	0.00	0.70
Year 2013	0.10	0.30	0.10	0.30	0.10	0.30	0.00	0.72
Year 2014	0.08	0.28	0.08	0.27	0.09	0.28	0.01	0.01
Year 2015	0.06	0.23	0.05	0.21	0.06	0.24	0.02	0.00
Year 2016	0.06	0.23	0.05	0.21	0.06	0.24	0.01	0.00
Year 2017	0.06	0.24	0.04	0.20	0.06	0.24	0.02	0.00

Year 2018	0.05	0.23	0.03	0.17	0.06	0.24	0.03	0.00
Year 2019	0.06	0.24	0.03	0.18	0.07	0.25	0.04	0.00
Year 2020 (Covid)	0.02	0.13	0.01	0.10	0.02	0.13	0.01	0.00
Region East Midlands	0.08	0.26	0.07	0.26	0.08	0.27	0.00	0.69
Region East of England	0.08	0.27	0.08	0.28	0.08	0.27	0.00	0.40
Region London	0.13	0.34	0.11	0.31	0.14	0.34	0.03	0.00
Region North East	0.03	0.18	0.04	0.20	0.03	0.18	-0.01	0.00
Region North West	0.13	0.34	0.13	0.34	0.13	0.34	0.00	0.44
Region Northern Ireland	0.01	0.09	0.01	0.11	0.01	0.08	0.00	0.00
Region Scotland	0.07	0.25	0.08	0.27	0.06	0.24	-0.02	0.00
Region South East	0.13	0.33	0.12	0.33	0.13	0.33	0.01	0.27
Region South West	0.10	0.29	0.12	0.32	0.09	0.29	-0.03	0.00
Region Wales	0.04	0.19	0.04	0.19	0.04	0.19	0.00	0.66
Region West Midlands	0.10	0.30	0.10	0.30	0.10	0.30	0.00	0.47
Region Yorkshire and The Humber	0.11	0.31	0.09	0.29	0.12	0.32	0.02	0.00
SIC group A	0.01	0.07	0.02	0.12	0.00	0.06	-0.01	0.00
SIC group B	0.00	0.03	0.00	0.02	0.00	0.03	0.00	0.30
SIC group C	0.13	0.33	0.04	0.19	0.15	0.35	0.11	0.00
SIC group D	0.00	0.03	0.00	0.01	0.00	0.03	0.00	0.06
SIC group E	0.01	0.08	0.00	0.05	0.01	0.09	0.01	0.00
SIC group F	0.06	0.24	0.02	0.15	0.07	0.26	0.05	0.00
SIC group G	0.27	0.45	0.41	0.49	0.24	0.43	-0.16	0.00
SIC group H	0.03	0.16	0.03	0.17	0.03	0.16	0.00	0.13
SIC group I	0.15	0.36	0.19	0.39	0.15	0.35	-0.04	0.00
SIC group J	0.05	0.21	0.01	0.08	0.05	0.23	0.05	0.00
SIC group K	0.01	0.08	0.00	0.03	0.01	0.09	0.01	0.00
SIC group L	0.02	0.13	0.01	0.11	0.02	0.13	0.01	0.01
SIC group M	0.08	0.27	0.07	0.26	0.08	0.27	0.01	0.03
SIC group N	0.06	0.24	0.03	0.16	0.07	0.26	0.05	0.00
SIC group P	0.02	0.13	0.01	0.12	0.02	0.13	0.00	0.20
	0.05	0.23	0.09	0.29	0.05	0.21	-0.05	0.00
SIC group R	0.03	0.17	0.02	0.13	0.03	0.18	0.02	0.00
SIC group S	0.03	0.17	0.05	0.22	0.02	0.15	-0.03	0.00

Notes:

The table shows the descriptive statistics for the whole sample and the subsamples of unincorporated and limited companies. The Unincorporated (Limited Companies) subsample includes companies without (with) company registered number. In the last two columns, the test for the difference in means between the sample of limited and unincorporated companies is presented – the p-value of the test statistic is shown in the last column.

Table 1.3 Test of differences in means for defaulted and non-defaulted companies (loans)

	Whole sample (N = 30,164)				Unincorporated (N = 5,781)				Limited companies (N = 24,383)			
	Defaulted	Non-defaulted	Difference	p-value	Defaulted	Non-defaulted	Difference	p-value	Defaulted	Non-defaulted	Difference	p-value
Small lender	0.06	0.05	0.01	0.00	0.08	0.04	0.05	0.00	0.05	0.05	0.00	0.52
Medium lender	0.15	0.17	-0.02	0.00	0.08	0.09	-0.01	0.55	0.16	0.18	-0.02	0.00
Large lender	0.79	0.79	0.01	0.35	0.83	0.88	-0.04	0.00	0.78	0.76	0.02	0.01
Unincorporated	0.19	0.19	-0.01	0.26								
Annual Turnover - real (CPIH)	1,091,780	1,556,207	-464,428	0.00	343,072	503,490	-160,418	0.00	1,264,263	1,808,230	-543,967	0.00
Real turnover <= 200k	0.33	0.21	0.11	0.00	0.53	0.38	0.15	0.00	0.28	0.17	0.11	0.00
Real turnover 200k - 500k	0.23	0.23	0.00	0.54	0.28	0.32	-0.04	0.00	0.22	0.21	0.01	0.31
Real turnover 500k - 1.2m	0.22	0.25	-0.03	0.00	0.15	0.23	-0.09	0.00	0.24	0.25	-0.01	0.02
Real turnover > 1.2m	0.22	0.31	-0.08	0.00	0.04	0.07	-0.02	0.00	0.27	0.36	-0.10	0.00
Age (years) at loan origination	6.77	9.10	-2.33	0.00	8.54	12.24	-3.71	0.00	6.36	8.35	-1.99	0.00
Age 0-3	0.49	0.37	0.12	0.00	0.49	0.36	0.13	0.00	0.49	0.37	0.12	0.00
Age 4-6	0.18	0.18	0.01	0.15	0.13	0.13	0.01	0.44	0.19	0.19	0.01	0.24
Age 7-10	0.14	0.17	-0.03	0.00	0.13	0.12	0.01	0.48	0.14	0.18	-0.04	0.00
Age > 10	0.19	0.28	-0.10	0.00	0.25	0.38	-0.14	0.00	0.17	0.26	-0.09	0.00
Loan Term	75.01	71.48	3.52	0.00	84.38	89.43	-5.05	0.00	72.85	67.19	5.66	0.00
Loan Amount - real (CPIH)	99,991	130,798	-30,807	0.00	58,069	85,521	-27,452	0.00	109,649	141,638	-31,989	0.00
EFG Interest Rate	6.88	5.67	1.20	0.00	7.30	5.76	1.55	0.00	6.78	5.65	1.13	0.00
Fixed interest rate	0.23	0.25	-0.02	0.00	0.29	0.28	0.01	0.61	0.21	0.24	-0.03	0.00
Loan Purpose: Asset Finance	0.00	0.01	-0.01	0.00	0.00	0.00	0.00	0.03	0.00	0.01	-0.01	0.00
Loan Purpose: Working Capital	0.43	0.35	0.09	0.00	0.28	0.18	0.09	0.00	0.47	0.38	0.09	0.00

Loan Purpose: Capital Investment	0.06	0.06	0.00	0.81	0.06	0.05	0.01	0.06	0.06	0.06	0.00	0.27
Loan Purpose: Growth	0.34	0.46	-0.12	0.00	0.48	0.65	-0.18	0.00	0.31	0.41	-0.10	0.00
Loan Purpose: Other	0.01	0.01	0.00	0.15	0.01	0.01	0.00	0.67	0.01	0.01	0.00	0.08
Loan Purpose: Start-up	0.16	0.12	0.04	0.00	0.18	0.10	0.08	0.00	0.15	0.12	0.03	0.00
No collateral	0.30	0.33	-0.03	0.00	0.67	0.58	0.09	0.00	0.22	0.27	-0.05	0.00
Year 2009 (GFC)	0.30	0.14	0.16	0.00	0.33	0.18	0.14	0.00	0.29	0.13	0.16	0.00
Year 2010	0.22	0.13	0.08	0.00	0.27	0.17	0.10	0.00	0.20	0.12	0.08	0.00
Year 2011	0.10	0.10	0.00	0.81	0.11	0.12	-0.01	0.14	0.09	0.09	0.00	0.57
Year 2012	0.07	0.09	-0.02	0.00	0.07	0.09	-0.02	0.02	0.07	0.09	-0.02	0.00
Year 2013	0.07	0.11	-0.04	0.00	0.06	0.11	-0.05	0.00	0.07	0.11	-0.04	0.00
Year 2014	0.06	0.09	-0.04	0.00	0.05	0.08	-0.03	0.00	0.06	0.10	-0.04	0.00
Year 2015	0.05	0.06	-0.02	0.00	0.03	0.05	-0.02	0.01	0.05	0.07	-0.02	0.00
Year 2016	0.05	0.06	-0.01	0.00	0.03	0.05	-0.02	0.01	0.05	0.06	-0.01	0.01
Year 2017	0.05	0.06	-0.01	0.00	0.03	0.05	-0.02	0.00	0.05	0.07	-0.01	0.00
Year 2018	0.03	0.06	-0.03	0.00	0.01	0.04	-0.03	0.00	0.04	0.07	-0.02	0.00
Year 2019	0.02	0.08	-0.05	0.00	0.01	0.04	-0.03	0.00	0.03	0.08	-0.06	0.00
Year 2020 (Covid)	0.00	0.02	-0.02	0.00	0.00	0.01	-0.01	0.00	0.00	0.02	-0.02	0.00

Notes:

The table presents the results of a univariate analysis for the whole sample and the subsamples of unincorporated and limited companies. The Unincorporated (Limited Companies) subsample includes companies without (with) company registered number. For each subsample, the means of variables for defaulted companies, non-defaulted companies, difference in means between defaulted and non-defaulted companies, and the p-value of t-test of differences between the means for defaulted and non-defaulted companies is presented.

Table 2 Cox's proportional hazard models determining loan defaults

	Whole sample			Unincorporated		Limited companies				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Small lender	1.345***	1.111	1.026	2.122***	1.416**	1.215***	1.072	1.024	0.987	1.001
Large lender	0.709***	1.003	1.000	0.727***	1.206	0.712***	0.975	1.016	0.964	0.989
Unincorporated	0.761***	0.778***	0.716***							
Real turnover 200k - 500k	0.899***	0.930**	0.932**	0.916	0.997	0.906**	0.919**	0.946	0.988	0.976
Real turnover 500k - 1.2m	0.847***	0.924**	0.925**	0.786***	0.877	0.869***	0.934*	0.966	1.075	1.046
Real turnover > 1.2m	0.733***	0.887***	0.886***	0.752**	0.936	0.736***	0.881***	0.862***	1.110*	1.050
Age 4-6	0.876***	0.846***	0.846***	0.826**	0.845*	0.878***	0.840***	0.934	0.916**	0.916**
Age 7-10	0.744***	0.732***	0.734***	0.868	0.930	0.723***	0.700***	0.799***	0.801***	0.802***
Age > 10	0.643***	0.666***	0.669***	0.642***	0.725***	0.647***	0.656***	0.771***	0.776***	0.785***
Loan Term		0.998***	0.998***		0.996***		0.998***	0.999**	0.998***	0.998***
Loan Amount - real (CPIH)		1.000***	1.000***		1.000		1.000***	1.000***	1.000	1.000
EFG Interest Rate		1.071***	1.072***		1.107***		1.068***	1.066***	1.060***	1.059***
Fixed interest rate		0.993	0.991		1.091		0.952	0.927*	0.915**	0.918*
Loan Purpose: Capital Investment		1.075	1.070		1.053		1.069	1.105	1.111	1.112*
Loan Purpose: Start-up		1.224***	1.216***		1.314***		1.186***	0.982	0.956	0.960
Loan Purpose: Working Capital		1.412***	1.406***		1.390***		1.402***	1.397***	1.380***	1.375***
No collateral		1.003	1.007		1.121*		0.948	0.973	0.972	0.977
Small Lender * Unincorporated			1.479***							
Large Lender * Unincorporated			1.066							
Distance to nearest branch								1.000		1.001*
Risk score								9963.1***		27.78***
Industry weight of evidence									0.763***	0.801***
Industry concentration (HHI ta)									0.994*	0.993**
Size of board (log)									0.768***	0.791***
Current liabilities to total liabilities - w1									1.449***	1.398***
P&L account reserve to total assets - w									0.619***	0.678***
Change in net worth									0.955**	0.973
Indicator of being audited									0.754***	0.754***
Indicator of charges on assets									1.101***	1.045
Late filing days									1.004***	1.003***
Indicator of subsidiary company - new									0.664***	0.685***
Board change									1.176***	1.123***
Share change									0.698***	0.681***

Non-missing pre-tax profit									0.949	0.947
Non-zero cash									0.782***	0.793***
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	30164	30164	30164	5781	5781	24383	24383	20536	20551	20536
Number of failures	7680	7680	7680	1438	1438	6242	6242	4885	4887	4885
Log pseudolikelihood	-75229.8	-74791.6	-74787.3	-11748.4	-11636.2	-59768.1	-59433.2	-45536.7	-45420.8	-45389.1
chi2 test statistic	2300.8	2791.6	2804.3	47774.2	35812.6	1806.9	2227.6	1952.7	2303.7	2345.9
Pseudo R-squared	0.0150	0.0207	0.0207	0.0227	0.0320	0.0146	0.0201	0.0232	0.0262	0.0264

Notes:

The table shows the estimation results for the Cox's proportional hazard models. The Unincorporated (Limited companies) subsample includes companies without (with) company registered number. The estimated coefficients are exponentiated and indicate hazard ratios. 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 3 Cox's proportional hazard models determining loan defaults excluding year 2009 (GFC) and 2020 (Covid)

	Whole sample			Unincorporated		Limited companies				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Small lender	1.287***	1.097	1.008	1.957***	1.369*	1.161**	1.061	1.030	0.974	0.993
Large lender	0.633***	0.940	0.940	0.601***	1.201	0.641***	0.910*	0.954	0.892*	0.927
Unincorporated	0.770***	0.801***	0.731***							
Real turnover 200k - 500k	0.886***	0.928*	0.930*	0.930	1.023	0.887***	0.917*	0.951	1.005	0.994
Real turnover 500k - 1.2m	0.816***	0.907**	0.909**	0.766***	0.907	0.834***	0.913*	0.938	1.067	1.044
Real turnover > 1.2m	0.677***	0.848***	0.847***	0.532***	0.786	0.683***	0.840***	0.817***	1.075	1.026
Age 4-6	0.850***	0.822***	0.822***	0.774**	0.793**	0.858***	0.822***	0.916*	0.917*	0.916*
Age 7-10	0.691***	0.681***	0.684***	0.794**	0.822*	0.674***	0.659***	0.749***	0.775***	0.773***
Age > 10	0.607***	0.638***	0.641***	0.590***	0.647***	0.620***	0.642***	0.763***	0.796***	0.800***
Loan Term		0.997***	0.997***		0.997**		0.998***	0.999**	0.998**	0.998**
Loan Amount - real (CPIH)		1.000***	1.000***		1.000**		1.000***	1.000***	1.000*	1.000*
EFG Interest Rate		1.067***	1.067***		1.118***		1.063***	1.062***	1.057***	1.056***
Fixed interest rate		1.004	1.003		1.154		0.957	0.931	0.919*	0.922*
Loan Purpose: Capital Investment		1.119*	1.107*		1.147		1.100	1.114	1.128	1.126
Loan Purpose: Start-up		1.212***	1.202***		1.212*		1.185***	0.935	0.915	0.918
Loan Purpose: Working Capital		1.368***	1.360***		1.266***		1.374***	1.369***	1.372***	1.368***
No collateral		1.001	1.010		1.148*		0.914*	0.906	0.876**	0.888*
Small Lender * Unincorporated			1.555***							
Large Lender * Unincorporated			1.058							
Distance to nearest branch								1.001		1.001**
Risk score								14122.2***		23.33***
Industry weight of evidence									0.839***	0.873***
Industry concentration (HHI ta)									0.998	0.997
Size of board (log)									0.757***	0.777***
Current liabilities to total liabilities - w1									1.383***	1.335***
P&L account reserve to total assets - w									0.621***	0.672***
Change in net worth									0.945**	0.961
Indicator of being audited									0.791**	0.796**
Indicator of charges on assets									1.159***	1.108***
Late filing days									1.003***	1.003***
Indicator of subsidiary company - new									0.688***	0.703***
Board change									1.154***	1.108**
Share change									0.553***	0.538***

Non-missing pre-tax profit									0.925	0.924
Non-zero cash									0.764***	0.775***
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	24217	24217	24217	4453	4453	19764	19764	16600	16613	16600
Number of failures	5393	5393	5393	967	967	4426	4426	3372	3373	3372
Log pseudolikelihood	-51693.5	-51396.1	-51391.0	-7629.2	-7552.0	-41513.5	-41282.9	-30786.5	-30714.9	-30696.9
chi2 test statistic	1606.4	1957.7	1984.3	410.4	570.6	1214.3	1528.7	1351.9	1491.5	1533.7
Pseudo R-squared	0.0150	0.0207	0.0208	0.0273	0.0371	0.0140	0.0195	0.0217	0.0243	0.0245

Notes:

The table shows the estimation results for the Cox's proportional hazard models for the sample excluding years 2009 (GFC) and 2020 (Covid). The Unincorporated (Limited companies) subsample includes companies without (with) company registered number. The estimated coefficients are exponentiated and indicate hazard ratios. 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 4 Selection models – probit

	Whole sample			Unincorporated			Limited companies		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Small lender	Medium lender	Large lender	Small lender	Medium lender	Large lender	Small lender	Medium lender	Large lender
Risk score							4.249***	0.757	-2.041***
Employment	0.00283**	0.000879	-0.00150**	0.0162*	0.00184	-0.00385	0.00207*	0.000642	-0.00102
Age (years) at loan origination	-0.00789***	-0.00689***	0.00863***	-0.0263**	-0.0154***	0.0234***	-0.000712	-0.00348*	0.00325*
Age (years) at loan origination squared	0.0000164	0.0000613*	-0.0000672	-0.0000183	0.000132**	-0.000208***	0.000000937	0.0000467*	-0.0000444*
Loan Term	-0.00975***	-0.00726***	0.00973***	-0.0152***	-0.00437***	0.00903***	-0.00704***	-0.00746***	0.00901***
Loan Amount - real (CPIH)	-0.00000827***	-0.000000573***	0.00000240***	-0.0000152***	0.000000503	0.00000195***	-0.00000765***	-0.000000694***	0.00000223***
Loan Amount - real (CPIH) squared	6.42e-12***	1.10e-12***	-2.62e-12***	1.31e-11***	2.62e-13	-2.83e-12***	5.70e-12***	1.24e-12***	-2.46e-12***
Loan Purpose: Asset Finance	0.287***	1.219***	0	-0.452	1.665***	0	0.536***	1.197***	0
Loan Purpose: Working Capital	-0.382***	0.703***	-0.482***	-0.523***	0.411***	-0.0472	-0.136*	0.731***	-0.654***
Loan Purpose: Capital Investment	0.0738	0.438***	-0.412***	0.0104	0.221*	-0.195**	0.293***	0.459***	-0.532***
Loan Purpose: Growth	-0.0950**	0.125***	-0.0343	-0.695***	-0.189**	0.528***	0.282***	0.182***	-0.256***
Loan Purpose: Other	-0.937***	0.893***	-0.592***	-0.293	0.101	0.193	-0.769***	1.053***	-0.854***
Year 2010	0.299***	0.191***	-0.237***	0.482***	0.119	-0.246***	0.274***	0.232***	-0.262***
Year 2011	0.155**	0.362***	-0.336***	0.368**	0.376***	-0.428***	0.157	0.357***	-0.340***
Year 2012	0.369***	0.195***	-0.255***	0.751***	-0.0412	-0.262**	0.363***	0.245***	-0.290***
Year 2013	0.355***	0.357***	-0.384***	0.754***	0.334***	-0.528***	0.241**	0.341***	-0.341***
Year 2014	0.529***	0.534***	-0.594***	0.969***	0.373***	-0.621***	0.467***	0.579***	-0.619***
Year 2015	0.548***	0.730***	-0.759***	1.151***	0.365***	-0.649***	0.544***	0.789***	-0.823***
Year 2016	0.751***	1.080***	-1.148***	1.216***	0.961***	-1.190***	0.738***	1.185***	-1.247***
Year 2017	0.734***	1.248***	-1.311***	1.115***	1.078***	-1.268***	0.741***	1.346***	-1.412***

Year 2018	1.053***	1.203***	-1.388***	1.330***	1.064***	-1.337***	1.129***	1.297***	-1.515***
Year 2019	1.284***	1.186***	-1.540***	1.318***	1.131***	-1.412***	1.382***	1.273***	-1.691***
Year 2020 (Covid)	1.292***	1.099***	-1.449***	1.384***	0.737***	-1.017***	1.567***	1.158***	-1.717***
Constant	-0.839***	-1.427***	0.821***	-0.128	-1.343***	0.402***	-1.483***	-1.526***	1.197***
Observations	30098	30098	29841	5751	5751	5737	20521	20521	20332
Pseudo R-squared	0.212	0.188	0.214	0.344	0.140	0.206	0.219	0.193	0.225

Notes:

The table shows the estimation results for the selection models. The Unincorporated (Limited Company) subsample includes companies without (with) company registered number. The coefficients are estimated using probit. 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 Cox's models with inverse Mills ratios

	Whole sample			Unincorporated		Limited companies				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
IMR small lender whole	0.746**	0.837	0.841							
IMR large lender whole	2.381***	1.269**	1.272**							
IMR small lender unincorporated				0.632**	0.541***					
IMR large lender unincorporated				2.908***	1.128					
IMR small lender limited						0.657**	0.642**	0.917	0.984	1.034
IMR large lender limited						2.863***	1.589***	1.316**	1.389***	1.339**
Small lender	2.119***	1.522	1.393	3.262***	4.080***	2.423***	2.392**	1.156	0.962	0.886
Large lender	0.161***	0.645**	0.644**	0.107***	0.974	0.122***	0.429***	0.614**	0.527***	0.581**
Unincorporated	0.782***	0.780***	0.737***							
Real turnover 200k - 500k	0.911***	0.934**	0.935*	0.957	0.995	0.994	0.976	0.950	0.991	0.977
Real turnover 500k - 1.2m	0.880***	0.936*	0.937*	0.837**	0.877	0.993	1.025	0.975	1.083	1.054
Real turnover > 1.2m	0.742***	0.898**	0.896**	0.795	0.960	0.832***	0.975	0.870***	1.117**	1.056
Age 4-6	0.855***	0.847***	0.847***	0.905	0.848*	0.934*	0.905**	0.934	0.916**	0.916**
Age 7-10	0.747***	0.737***	0.739***	0.975	0.937	0.785***	0.758***	0.804***	0.807***	0.807***
Age > 10	0.671***	0.672***	0.675***	0.790***	0.746***	0.721***	0.709***	0.772***	0.779***	0.786***
Loan Term		0.999**	0.999**		0.998		1.001	1.000	0.999	0.999
Loan Amount - real (CPIH)		1.000***	1.000***		1.000		1.000***	1.000***	1.000	1.000
EFG Interest Rate		1.068***	1.068***		1.099***		1.063***	1.063***	1.057***	1.057***
Fixed interest rate		1.008	1.006		1.130		0.948	0.946	0.933	0.936
Loan Purpose: Capital Investment		1.028	1.022		0.922		1.048	1.072	1.074	1.079
Loan Purpose: Start-up		1.230***	1.222***		1.162		1.061	1.013	0.991	0.988
Loan Purpose: Working Capital		1.356***	1.351***		1.359***		1.372***	1.338***	1.305***	1.304***
No collateral		1.000	1.006		1.137**		0.953	0.969	0.970	0.972
Small Lender * Unincorporated			1.454**							
Large Lender * Unincorporated			1.033							
Distance to nearest branch								1.001		1.001**
pd_ensemble								7983.8***		23.62***
Industry weight of evidence									0.762***	0.797***
Industry concentration (HHI ta)									0.994*	0.993**
Size of board (log)									0.774***	0.796***
Current liabilities to total liabilities - w1									1.446***	1.400***
P&L account reserve to total assets - w									0.622***	0.676***
Change in net worth									0.958*	0.974
Indicator of being audited									0.756***	0.756***

Indicator of charges on assets									1.094***	1.041
Late filing days									1.004***	1.003***
Indicator of subsidiary company - new									0.666***	0.685***
Board change									1.173***	1.123***
Share change									0.710***	0.694***
Non-missing pre-tax profit									0.941	0.939
Non-zero cash									0.780***	0.790***
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	29841	29841	29841	5737	5737	20332	20332	20317	20332	20317
Number of failures	7641	7641	7641	1432	1432	4863	4863	4861	4863	4861
Log pseudolikelihood	-74634.3	-74353.9	-74349.5	-11642.7	-11576.1	-45605.2	-45432.9	-45276.2	-45160.6	-45129.0
chi2	2325.8	2821.2	2838.3	537.7	22884.9	1539.7	1747.3	1983.4	2322.8	2367.9
Pseudo R-squared	0.0171	0.0208	0.0208	0.0268	0.0324	0.0167	0.0204	0.0233	0.0263	0.0265

Notes:

The table shows the estimation results for the Cox's proportional hazard models with the inverse Mills ratios controlling for potential self-selection. The inverse Mills ratios were computed using the predicted values based on the probit models presented in Table 4. The Unincorporated (Limited companies) subsample includes companies without (with) company registered number. The estimated coefficients are exponentiated and indicate hazard ratios. 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.

Figure 1 Number of deals

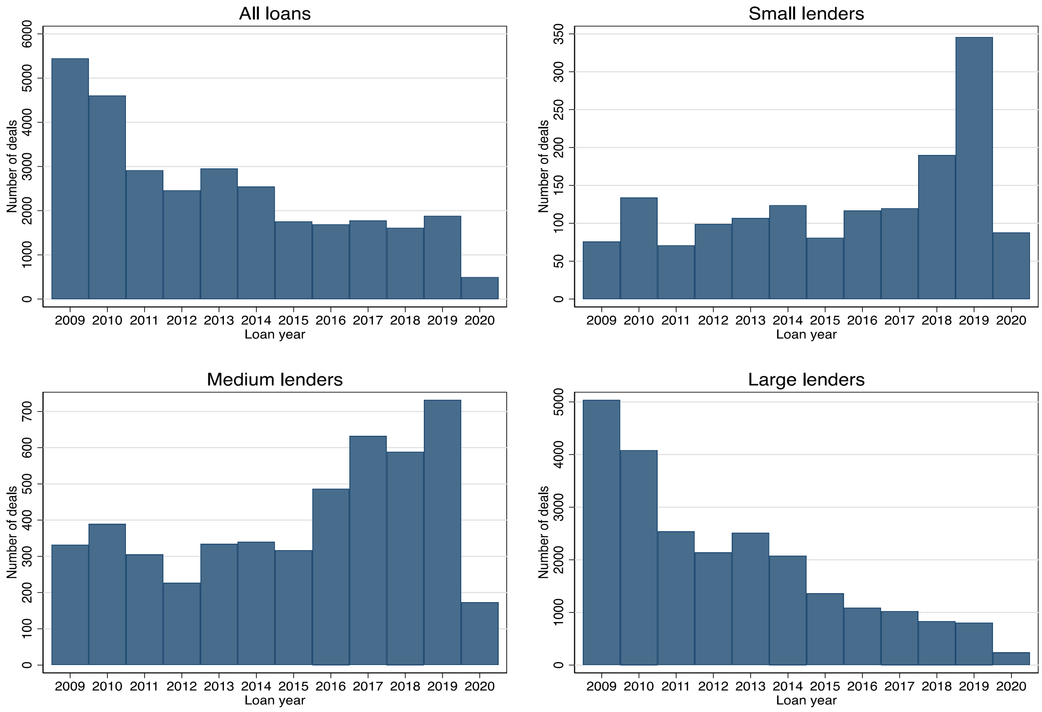
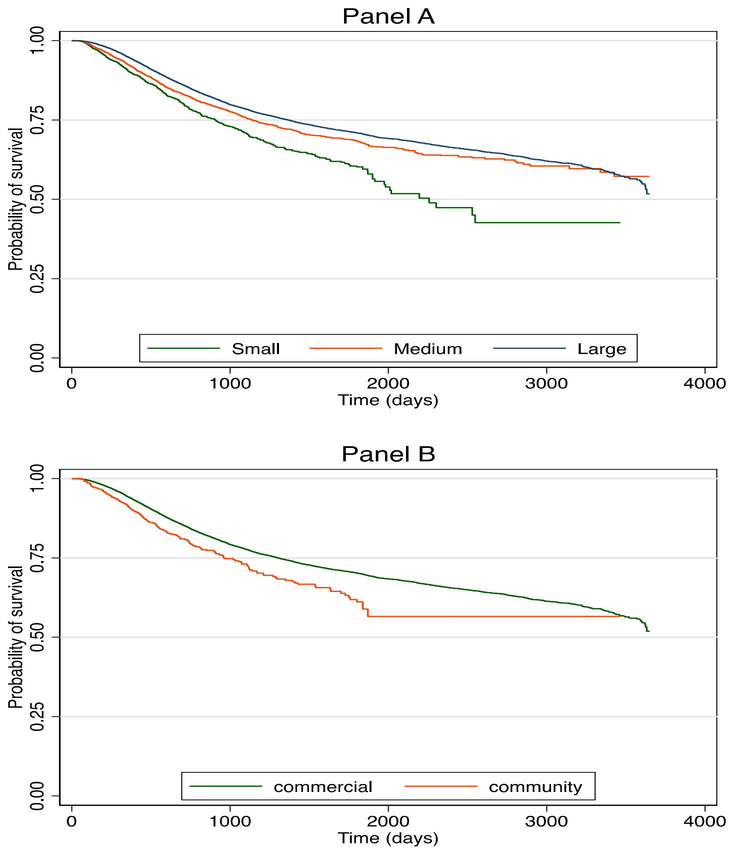


Figure 2 Kaplan-Meier estimates of survival function



Censoring date 14/6/2021

Appendix

Table A1 Company population insolvency risk models: Subsamples based on company status (micro entity, abridged accounts, full accounts) and industry sector

	Micro					Abridged					Full accounts	
	All	All	Sector 1	Sector 2	Sector 3	Sector 4	Sector 5	Sector 6	Sector 7	Sector 8	All	Manufact.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Independent variables	Insolvent	Insolvent	Insolvent	Insolvent	Insolvent	Insolvent	Insolvent	Insolvent	Insolvent	Insolvent	Insolvent	Insolvent
Total assets (log)	0.332***	0.321***	0.308***	0.305***	0.340***	0.331***	0.260***	0.450***	0.377***	0.355***	0.0706***	0.0272*
Indicator of large company	-1.471***	-1.203***	-1.094***	-1.440***	-0.774***	-1.000***	-0.883***	-2.644***	-1.756***	-1.577***	-0.532***	-0.549***
Industry weight of evidence	-0.753***	-0.668***	-0.914***	-0.940***	-0.885***	-0.488***	-0.745***	-1.165***	-0.742***	-0.597***	-0.684***	-0.960***
Industry concentration (HHI ta)	0.00582***	0.00499***	0.00101	-0.00186**	0.221***	0.0691***	0.00291	0.00279	0.0153	0.00314***	0.00245***	0.00577***
Age in years (log)	-0.140***	-0.167***	-0.141***	-0.118***	-0.143***	-0.146***	-0.313***	-0.247***	-0.225***	-0.107***	-0.120***	-0.0374*
Indicator of age from 3 to 8 years	0.0798***	0.0547***	0.0685	-0.0941***	0.0742***	0.00928	0.0565***	0.230***	0.0627***	0.101***	0.0810***	0.0185
Size of board (log)	-0.351***	-0.368***	-0.447***	-0.379***	-0.378***	-0.337***	-0.314***	-0.390***	-0.341***	-0.430***	-0.281***	-0.166***
Working capital to total assets	0.110***											
Current assets to total assets	0.492***											
Current liabilities to total liabilities	1.226***											
P&L account reserve to total assets	-0.826***	-0.902***	-1.096***	-0.896***	-0.863***	-1.027***	-1.084***	-0.561***	-0.811***	-0.956***	-0.317***	-0.423***
Net worth to total assets	-0.538***	-0.290***	-0.0225	-0.312***	-0.517***	-0.169***	-0.0745**	-0.312***	-0.239***	-0.193***	-0.292***	-0.405***
Short-term liabilities to total assets	0.707***	0.522***	0.998***	0.444***	0.344***	0.587***	0.611***	1.006***	0.529***	0.646***	0.215***	0.107
Change in net worth	-0.189***	-0.207***	-0.207***	-0.335***	-0.147***	-0.320***	-0.203***	-0.116***	-0.163***	-0.174***	-0.0417***	-0.0411
Indicator of being audited	-0.331***	-0.186***	-0.309***	-0.221***	-0.150***	-0.212***	-0.235***	-0.215***	-0.265***	-0.195***	-0.192***	-0.244***
Audit qualification (going concern or severe)	0.951***	0.900***	0.925***	1.006***	0.747***	1.035***	0.875***	0.883***	0.790***	1.021***	1.208***	1.103***
Indicator of charges on assets	0.595***	0.513***	0.761***	0.732***	0.185***	0.699***	0.261***	0.736***	0.666***	0.531***	0.575***	0.750***
Late filing days	0.00526***	0.00476***	0.00636***	0.00411***	0.00518***	0.00463***	0.00524***	0.00485***	0.00442***	0.00479***	0.00458***	0.00397***
Indicator of subsidiary company	-0.440***	-0.386***	-0.534***	-0.317***	-0.254***	-0.460***	-0.191***	-0.629***	-0.488***	-0.400***	-0.300***	-0.280***
Board change	0.392***	0.461***	0.427***	0.439***	0.533***	0.463***	0.401***	0.357***	0.405***	0.434***	0.283***	0.302***
Share change	0.229***	0.196***	-0.0480	0.0632	-0.0649	0.140**	-0.0211	0.242***	0.338***	0.0421	0.216***	0.164**
Non-missing pre-tax profit	0.0492***											
Non-zero cash	-0.314***											
GDP growth (FRED)	-0.00697***	0.0190***	0.0168	0.0129***	0.0142***	0.0245***	0.0188***	0.0364***	0.0171***	0.0319***	0.000679	0.0380***
Net lending - 3 months growth (BoE)	-0.0140***	-0.0102***	-0.00964***	-0.0127***	-0.0111***	-0.00731***	-0.00611***	-0.00971***	-0.00559***	-0.00972***	0.00288***	0.00241
Real interest rate	0.0778***	0.0252***	0.0317*	0.0419***	0.00548	0.00250	-0.0197*	0.0133	0.0305***	0.0129**	0.0724***	0.106***
1 - Fixed assets to total assets		0.779***	1.139***	0.645***	0.317***	0.761***	0.731***	0.973***	1.057***	0.886***	0.710***	0.339***
Cash to total assets		-1.292***	-0.680***	-2.880***	-0.650***	-2.114***	-1.195***	-1.561***	-1.397***	-1.486***	-1.617***	-2.443***
Inventories to total assets		-0.245***	0.0608	0.132*	0.350***	0.0707	0.695***	-0.264***	-0.0553	0.0425	-0.488***	-0.0525
Trade debtors to total assets		0.498***	0.125	0.311***	1.355***	0.331***	0.190**	-0.0906	0.156***	0.306***	0.0815**	0.0151
Trade creditors to total liabilities		0.965***	1.360***	0.755***	0.781***	0.916***	1.134***	1.276***	1.037***	1.060***	0.631***	0.810***
Return on assets											-0.169***	-0.150**
Retained earnings to total assets											-3.853***	-5.691***
Interest coverage											-0.000993***	-0.00118***
Sales to total assets											0.0266***	0.0277***
Constant	-9.495***	-9.125***	-9.777***	-8.733***	-9.799***	-9.366***	-8.231***	-10.32***	-9.714***	-9.491***	-5.409***	-5.339***
Observations	21612505	16549867	365786	1198274	3556454	2515271	605632	1651101	4512209	2145140	2630879	259300
McFadden pseudo-R2	0.0971	0.110	0.127	0.133	0.119	0.0944	0.0881	0.103	0.107	0.108	0.125	0.162
Estimation year	**1998-2018**	**1998-2018**	**1998-2018**	**1998-2018**	**1998-2018**	**1998-2018**	**1998-2018**	**1998-2018**	**1998-2018**	**1998-2018**	**1998-2018**	**1998-2018**
Default rate (estimation)	0.0101	0.0111	0.00658	0.0189	0.0117	0.0132	0.0207	0.00718	0.00944	0.00786	0.0106	0.0177
Defaulted (positive)	218200	170164	2202	21271	38244	31009	11511	11054	39410	15463	26340	4385
True positive	154067	124643	1598	16174	28467	22169	7851	7712	28137	11222	19414	3386
True positive rate	0.706	0.732	0.726	0.760	0.744	0.715	0.682	0.698	0.714	0.726	0.737	0.772
Non_defaulted (negative)	21394305	15126936	332589	1102492	3220548	2311104	545157	1527918	4135893	1951235	2451638	242874
True negative	15258390	10776815	250759	778407	2297387	1605598	380277	1127635	2998970	1395476	1782633	180610
True negative rate	0.713	0.712	0.754	0.706	0.713	0.695	0.698	0.738	0.725	0.715	0.727	0.744
AUC (estimation sample)	0.778	0.787	0.810	0.804	0.795	0.768	0.754	0.791	0.784	0.792	0.803	0.831
Holdout year	**2019-2020**	**2019-2020**	**2019-2020**	**2019-2020**	**2019-2020**	**2019-2020**	**2019-2020**	**2019-2020**	**2019-2020**	**2019-2020**	**2019-2020**	**2019-2020**
Defaulted (positive)	5980	3380	53	363	651	609	364	188	764	388	319	29
True positive	3880	1836	36	200	322	323	209	84	399	217	216	20
True positive rate	0.649	0.543	0.679	0.551	0.495	0.530	0.574	0.447	0.522	0.559	0.677	0.690
Non_defaulted (negative)	2666203	1249387	30942	74148	297011	172549	48600	111941	336142	178054	152582	12012
True negative	1929416	1058617	26039	61737	265061	142706	37474	93634	283271	147206	122960	10319
True negative rate	0.724	0.847	0.842	0.833	0.892	0.827	0.771	0.836	0.843	0.827	0.806	0.859
AUC (holdout sample)	0.749	0.783	0.848	0.806	0.799	0.767	0.738	0.720	0.760	0.774	0.816	0.868

* p<.1, ** p<.05, *** p<.01

Notes:

The tables presents the estimation results for the risk score models estimated using the panel of UK corporate data comprising over 25 million company-year observations. The dependent variable is the indicator of exit by insolvency. The estimation period covered years from 1998 to 2018. The coefficients are estimated using logistic regression. The subsamples Micro, Abridged and Full Accounts are defined by the scope of accounting information submitted by the companies. The industry sectors for the subsample Abridged are based on industry sections using 2-digit SIC codes and Statistical classification of economic activites in the European Community. Sector 1 includes sections A, B, D, E; sector 2 includes section C; sector 3 sections F and L; sector 4 sections G and H; sector 5 section I; sector 6 section J; sector

7 sections M and M; and sector 8 sectios O and U. The manufacturing sector in Full accounts subsample refers to section C. 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 A2 Profile of EFG recipients in the private company population

Firm Characteristics	Models Predicting the Probability of Loan Gaurantee Scheme (EFG) Borrowing							
age years <3	**0.746**	**0.000**	**0.807**	**0.000**	**0.830**	**0.000**	**0.878**	**0.000**
age years 4-7	0.224	0.000	0.463	0.000	0.463	0.000	0.532	0.000
age years 8 -11	0.306	0.000	0.457	0.000	0.459	0.000	0.460	0.000
age years 12-15	0.202	0.000	0.310	0.000	0.305	0.000	0.266	0.000
size_micro	1.909	0.000	1.913	0.000	1.864	0.000	1.846	0.000
size_small	**2.855**	**0.000**	**2.933**	**0.000**	**2.686**	**0.000**	**2.707**	**0.000**
size_medium	2.067	0.000	2.171	0.000	1.823	0.000	1.837	0.000
Change in Directors	-0.164	0.000	-0.021	0.343	-0.200	0.000	-0.225	0.000
Change in shareholders	0.897	0.000	0.841	0.000	0.595	0.000	0.634	0.000
Creditor Charge on Assets	1.212	0.000	1.355	0.000	0.961	0.000	1.016	0.000
Knowledge Intensive Firms	-6.088	0.000	-6.112	0.000	-7.100	0.000	-7.177	0.000
OA-Cosmopolitan	0.912	0.000	1.020	0.000	1.056	0.000	1.076	0.000
OA-Ethnicity	1.097	0.000	1.171	0.000	1.192	0.000	1.199	0.000
OA-Multicultural Metropolitan	1.135	0.000	1.158	0.000	1.192	0.000	1.186	0.000
OA- Urbanites	1.278	0.000	0.915	0.000	0.669	0.000	0.676	0.000
OA-Suburban	0.323	0.000	0.337	0.000	0.380	0.000	0.391	0.000
OA-Constrained City	0.337	0.000	0.360	0.000	0.386	0.000	0.391	0.000
OA-Hard Pressed	0.361	0.000	0.355	0.000	0.399	0.000	0.396	0.000
Company Risk Score					**7.785**	**0.000**	**8.101**	**0.000**
GFC Dummy	**1.240**	**0.000**	**1.010**	**0.000**	**1.191**	**0.000**		
GDP Growth			-0.017	0.000			-0.074	0.000
Growth in Net Lending			-0.043	0.000			-0.062	0.000
Real Interest rates			-0.059	0.000			-0.193	0.000
Industry Dummies								
Regional Dummies								
Constant	-22.686	0.426	-23.539	0.409	-8.724	0.796	-7.611	0.821
Observations	25261544		25261544		17819235		17819235	
EFG Firms	25307		22901		21611		21578	
Classification Accuracy	84.60%		85.50%		80.80%		80.10%	

Notes:

The tables presents the estimation results for the logit models estimated using the panel of UK corporate data comprising over 25 million company-year observations. The dependent variable is the indicator of EFG loan. The estimation period covered years from 1998 to 2020. The coefficients are estimated using logistic regression. 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).