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Cost of debt, loan default, and the effects of a public loan guarantee on high-tech firms

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Abstract

High-technology firms *per se* are perceived to be more risky than other, more conventional, firms. It follows that financial institutions will take this into account when designing loan contracts, and that this will manifest itself in more costly debt. In this paper we empirically test whether the provision of a government loan guarantee fundamentally changes the way lenders price debt to high-tech firms. Further, we also examine whether there are differential loan price effects of a public guarantee depending on the nature of the firms themselves and the nature of the economic and innovation environment that surrounds them. Using a large UK dataset of 29,266 guarantee backed loans we find that there is a high-tech risk premium which is justified by higher default, but, in general, that this premium is altered significantly when a public guarantee is provided for all firms. Further, all these loan price effects differ on precise spatial economic and innovation attributes.

Keywords: cost of debt, high-tech firms, public loan guarantee scheme, loan default

JEL CODE: G21, G28

1. Introduction

Whilst there are clear economic benefits from innovation and technological advancement (Laeven et al., 2015), innovation processes are highly uncertain in their outcomes (Jalonen, 2012; Scherer et al., 2001). This means that financiers will view funding projects associated with these efforts with caution. As small firms in general face a penalty due to their smallness *per se*, associated with the relatively high fixed costs of lending (and of providing equity) and asymmetric information problems, being innovative and technologically driven adds a further layer of asymmetry and informational opacity (Carpenter and Petersen, 2002; Guiso, 1998; Hall, 2002; Himmelberg and Petersen, 1994; Ughetto, 2008). In short, the literature predicts that in debt markets, smaller firms already face general access problems and pay a premium on borrowing – but these problems may be worse for high-technology firms (Berger et al., 2007; Hall and Lerner, 2010).

Whilst governments have intervened in this small business finance space explicitly to correct for perceived market failures, or gaps in provision, in many ways, including loan guarantee schemes (Cowling, 2010; Honohan, 2010; Ughetto et al., 2017), R&D tax credits (Cowling, 2016), grants, soft loans, hybrid equity schemes (Aernoudt, 2005; Cannone and Ughetto, 2014), and business angel schemes (Ramadani, 2009), the general approach to the financing of innovative and technology based firms has favored equity funding and intervention in equity capital markets (Kortum and Lerner, 2000; Langeland, 2007). This has largely ignored the potential role that debt (Kerr and Nanda, 2014) and particularly loan guarantees might play in the funding of technology based firms. This is interesting in itself as the purpose of a public loan guarantee is to reduce the (default) risk to the lender of providing a loan to an informationally opaque smaller business (Honohan, 2010). In fact, the numerous loan guarantee programs introduced around the world have been conceived to allow lenders to share with the government the risk of default on outstanding loans, with the latter partially or totally covering any potential loss (Beck et al., 2010; Boschi et al., 2014; Cowling and Mitchell, 2003; Honohan, 2010). These public guarantee instruments, although differing in their characterizing features across nations (i.e. percentage of guaranteed coverage, lending criteria, industry and geographical limitations, loss distribution policy), share the common aim of reducing the barriers to additional finance for borrowers that mostly suffer from credit constraints (Cowling and Siepel, 2013)[1].

To the best of our knowledge no empirical works have investigated, in the context of publicly guaranteed schemes, the dynamics of loan pricing and loan default when borrowers are high-tech firms. In particular, we are not aware of any study examining to what extent small high-tech firms face higher default rates and a greater cost premium for the use of debt finance compared to their non high-tech peers when lending is guaranteed by government. On the one side, it is expected that banks charge a higher cost of capital to high-tech firms because of their higher risk, uncertain returns, and lack of collateral assets. On the other hand, the presence of the public guarantee should somehow attenuate such "innovation debt penalty". The paper adds to extant literature in two respects. First, it is the first study to investigate whether the presence of a government backed loan guarantee alters banks view in respect of the loan risk-premium charged to high-tech firms. Second, it differentiates from previous works in the field because it questions whether there is any spatial variation in both the cost of loans to high-technology firms and in their default rates.

In this paper we explore several key aspects of lending to technology based smaller businesses, using a large UK dataset of 29,266 loans issued under the Small Firm Loan Guarantee (SFLG) public Scheme. The scheme, established in 1981 by the UK Government, targets young and small businesses (up to five years old and with an annual turnover of up to £5.6 million) that lack track records or collateral to secure loans and has been conceived in eight distinct phases.

Our analysis, which concentrates on the phases VI and VII of the Scheme (2000-2005), is twofold. Firstly, we quantify whether high-tech firms have a higher default risk than more conventional firms, and whether they face a double-hurdle of being small and being innovative in respect of the price premium they pay on their borrowing, when lending is guaranteed by government (Lee et al., 2015).

[1] However, it has been found that the "credit additionality" effect induced by such schemes may not be achieved when the government coverage falls below a certain threshold (Boschi et al., 2014).

Indeed, we test the presence of a differential effect in terms of the loan price charged by banks for high-tech firms compared to their more conventional small firm peers. Secondly, we are able to trace out more nuanced loan price effects relating to the specific loan contract terms, the spatial location of the firms and the competitive, innovative and economic environment that surrounds them. In doing so we hope to build upon a growing body of research that has begun to unravel some key questions relating to innovation financing in the context of public loan guarantee programmes (see Cincero and Santos, 2015).

The rest of the paper is set out as follows. Firstly, we review the literature in several related areas including small firm and high-technology firm financing, also in the context of guaranteed lending, and the effects of economic geography on the financing outcomes of smaller firms. Secondly, we discuss the empirical data and present the basic sample descriptive statistics. We then present our empirical modelling of the loan spread (our measure of the price of lending) and of loan default (our measure of loan riskiness) under the UK policy intervention scheme. We conclude by summarizing our findings and setting this in the context of previous literature. Public policy impacts and implications are also discussed given the centrality of publicly supported loan guarantee schemes in the small business finance arena.

2. Literature review

2.1 The financing of high-technology firms

There are longstanding concerns that high-technology or innovative firms may find themselves credit constrained (Revest and Sapio, 2010; Ughetto, 2008; Westhead and Storey, 1997). Work in this area has focused on several explanations. The most important is asymmetric information (Burgstaller, 2013). In the classic explanation of credit constraints for small firms, Stiglitz and Weiss (1981) argued that information asymmetries may cause adverse selection in credit markets making it rational for borrowers to restrict lending to certain types of firms, rather than raising the price of loans. In a similar manner to the classic 'market for lemons' (Akerlof, 1970), higher loan costs drive out the better quality applicants, lowering average quality and leading lenders to restrict financing. For innovative firms, this problem of asymmetric information is mitigated by patenting, which provides an indicator of the quality of innovation to the lender and so reduces loan spreads (Francis et al., 2012; Plumlee et al., 2015).

Yet three additional factors might make it costlier to lend to innovative firms and so raise bank margins. The first is that the expected future revenues arising from investments in scientific and technological research are uncertain. Secondly, an evaluation of the quality and strength of intellectual property rights is expensive and often requires specialist expertise, thus adding to the per unit cost of lending. To some degree, the second is the related challenge of raising collateral. Intangible assets such as new products are hard to value and so difficult to use as collateral (Mina et al., 2013). The third is the reluctance of innovative firms to reveal information to the market for valuation and so forced to rely on internal finance (Magri, 2009). These factors raise screening costs for lenders, making it hard to overcome the information problems identified by Stiglitz and Weiss (1981).

A second explanation is the idiosyncratic nature of risk in the development of new, innovative products (Mina et al., 2013). By their nature, investments in R&D, new products or processes are risky activities – while some such investments will pay off, the majority yield relatively little return (Carpenter and Petersen, 2002; Coad and Rao, 2008; Hall, 2002). Moreover, high-technology firms may be seeking finance for R&D which is more speculative still (Westhead and Storey, 1997). While funders taking equity stakes may be interested in the long-term value of the company, banks are principally interested in the simple ability of lenders to repay and benefit little beyond the repayment of a loan if a product is highly successful.

Empirical work has shown a strong link between banking and technological progress. For example, Amore et al. (2013) show that the deregulation and greater banking competition is associated with increased innovation. Similarly, Hsu et al. (2015) use patenting data to show that firms which have a strong patent portfolio pay lower spreads. However, these studies tend to focus on patenting – an output measure of innovation, which reflects investments in research and development (R&D) which have already been made. In contrast, firm level studies considering firms involved in regular innovative activity often show that innovative firms are more credit constrained. Both Freel (2007) and Lee et al. (2015) find that innovative small firms are more likely to be rejected when applying for bank loans. The precise indicator of innovation seems to matter. But while several studies have considered alternative types of innovation, relatively few studies have considered high-technology firms explicitly. This is important as the link between the firm and the industry is more closely aligned in respect of high-technology, and this in turn more closely maps into the way banks make lending allocation decisions. While the categorization of firms into high-tech and low-tech may cast some firm-level heterogeneity in innovation and R&D propensities, it has been established that banks make annual strategic lending choices at the industry sector level in terms of their broad allocation of credit (see Cowling, 2010 for the UK context). Capital in this sense flows to industries, not firms *per se*.

2.2 Geographical context and financing high-technology firms

Despite this evidence base, relatively fewer studies have considered regional variation in these patterns of financing. However, there is increasing interest in the idea that regional factors, such as the level of banking development or innovation intensity may matter for firm financing (Crocco et al., 2012; Munari and Toschi, 2015). Studies on IPO's, for example, suggest that underpricing is more likely the further the firm is located from the financial capital (Acconcia et al., 2011). This is an important question, as the availability of firms to access finance is seen as an important determinant of subsequent economic growth – with empirical evidence suggesting finance is particularly important in deprived regions (Craig et al., 2008).

One theoretical position in this area is that distance between providers of finance and potential borrowers may hinder exchanges of information and make it harder for firms to access the finance they need (Ughetto, 2009). With regard to equity finance, the classic Silicon Valley venture capitalists are stereotypically imagined to follow a '2 hour rule' where they are unwilling to make investments beyond from their headquarters because doing so increases the cost of monitoring investments. Empirical work does support the idea of local bias in venture capital investments, although this is particularly the case for younger VCs (Cumming and Dai, 2010).

Building on a similar institutional framework, equity stakes are seen as being geographically limited, meaning that firms in 'core regions' find it easier to access finance than those in peripheral areas. Essentially, the clustering of investment activity in particular cities and regions may create a self-reinforcing bias towards these areas, with both investment opportunities and specialist investors clustering in technologically advanced regions. These 'thick-markets' for specialist finance will be reflected in both the demand and supply of finance. Yet, this might mean that the relatively few investment opportunities which arise in relatively low-tech regions are actually a higher quality. In their study of VC investments in the US, Chen et al. (2010) show investments made outside of the core regions are rarer but, because they have to be higher quality, more profitable on average.

While there is good evidence on the link between information and equity investments, fewer studies have considered the relationship between banks and the geography of innovative firms finance (Lee and Brown, 2016). One approach to explaining why banks may be less likely to lend to innovative firms in particular regions lies in the distinction between soft information, non-codified information about the firm which is hard to transmit electronically and is often developed through face to face contact, and hard information, such as credit records or company accounts, which can easily be transmitted from place to place. A simple explanation for regional variation in the financing of high technology firms is that persuading finance providers of the merits of innovative high-technology projects may require soft information, and this soft information may be locally bound. Banks focusing on high-technology industries may focus more on soft rather than hard information in their lending decisions. For example, Brown et al. (2012) show that banks do not use credit rating information to the same degree when evaluating lending applications from high-technology firms, although high-tech firms still face greater difficulties in accessing finance than low-tech firms.

There are several grounds for criticism of this approach. In the first place, the distinction between soft and hard information may not be as simple and clear-cut as portrayed (Wojcik, 2011). But it may also be that the structure of the banking sector in particular regions is more important than simple distance. For example, Alessandrini et al. (2009) suggest that the more hierarchical levels there are in a bank, the harder it will be to exchange soft information, and so this functional distance would matter for innovation as much as actual geographical distance. They show that firms in Italian regions where the banking system is functionally distant are less likely to introduce new innovations, with firms further from core banking centres financially constrained. In contrast, the regional share of big banks did not seem to matter. Similar evidence is presented for Austrian districts by Burgstaller (2013) who finds that higher bank competition is associated with lower margins, although the author does not focus on high-technology firms specifically.

A second set of potential explanations focus on the development of specialist spatial industries and markets to serve the investment and general financing requirements of high-tech firms. Classic explanations of innovation ecosystems show inter-related sets of financiers, entrepreneurs and other institutions developing together. However, in regions with few innovative firms' these synergies may not operate and thin-markets for specialist finance may develop as increased search costs make it uneconomic for providers to operate (Nightingale et al., 2009). Reflecting this, Chen et al. (2010) show that venture capitalists in the United States tend to invest in areas where past investments have been successful, and that the most successful investment firms tend also to be located in these core areas. The corollary of this is that banks in regions with high shares of tech firms may develop specialist lending facilities, such as those offered by banks in high-technology clusters such as Tech City. This might mean that the share of high-technology firms in a region is associated with a reduced cost of borrowing, as banks become better at screening borrowers.

Similarly, others have been concerned about the relationships with regional development. Financing of high-technology firms has a two-directional relationship with regional development, with availability of finance both a cause and a consequence of regional growth. While some studies have considered this in the UK case, the evidence is mixed. Westhead and Storey (1997) show no evidence that high-technology firms in assisted areas (deprived regions) of Britain are more likely to be financially constrained. In contrast, Lee and Brown (2016) show that innovative companies in less affluent UK areas are particularly likely to report rejection rates.

2.3 Loan Guarantee Schemes

Governments in more than one hundred countries across the developed and developing world operate loan guarantee schemes (often called partial credit guarantee schemes, PCGs) (Beck et al., 2010). The pervasiveness of loan guarantee schemes as a primary instrument to promote SME lending implicitly assumes that there is a market failure in the provision of debt finance to SMEs, and, that by altering the risk-return payoff for private banks, private banks will increase their willingness to lend to informationally opaque and/or asset poor SMEs with viable funding proposals (Cowling, 2010; Cowling and Siepel, 2013; Honaghan, 2008). The key parameter in terms of changing the banks risk-return function is the coverage ratio, the proportion of the loan advanced by the private bank guaranteed by the government in the event of borrower default (Beck et al., 2010). Across the seventy six guarantee schemes covered in the 2008 World Bank review, the median coverage (guarantee) ratio was 80%. A later World Bank study of MENA countries (Saadani et al., 2011) found a slightly lower median guarantee of 75%. The guarantee level ensures that part of the lending risk is shared by the bank thus increasing their incentives to properly conduct due diligence at the point of loan application and to monitor successful loan applications, both of which act to reduce expected losses arising from loan default.

The outcome evidence base is growing, but not as complete as would be required to make a comprehensive judgement on the generalizable efficacy of loan guarantee programmes as a policy instrument. Context is clearly important and the specific nature of spatial capital markets and scheme parameters have a decisive impact on the outcomes achieved. The first issue we concern ourselves with is finance additionality, or in North America incrementality. Evidence from the UK schemes found that scheme additionality was increasing over time as the target groups became more focused and lending banks were subject to greater scrutiny. The 1999 UK evaluation (KPMG, 1999) estimated that 70% of loans were additional in that firms could not have accessed any market based debt finance. This increased to 79% in the 2010 UK evaluation (Cowling, 2010), and 82% in the 2013 UK evaluation (Allinson et al., 2013). Comparable estimates for the Canadian scheme (Riding et al., 2007) reported a figure of 74.8% additionality. On job creation, the evidence that guarantee schemes can be associated with net job creation is fairly strong. For the US, Brown and Earle (2016) find that the net cost per job created over two decades was US$ 21,000 – 25,000, and that these effects were stronger for younger firms and when local credit conditions are weak. UK evidence found that net jobs cost averaged £5,500 - £10,000 per job created (Cowling, 2010) and that on average each supported firm created 0.4 jobs per annum, which was smaller than the later evaluation which reported 0.96 net jobs per firm per annum (Allinson et al., 2013). Both French (Lelarge et al., 2010) and Norwegian evidence (Poyry, Damwad, Agenda Kampang, 2010) also supported the job creation success of guarantee schemes. On loan default, UK estimates report 3 year loan default figures of 33.3% for SFLG and 28.0% for Enterprise Finance Guarantee (EFG), the newer scheme. The French scheme increased default by 6.2 percentage points compared to normal lending, and estimates for the Italian scheme suggest a 2.5% increase in default. But, importantly, the costs of default were not proportional to the actual default rate. UK estimates show that default cost was only 17.2% of total loan value which implies a net cost per recipient of only £5,000.

3. Dataset and descriptive statistics

The data we used in this study include the loans issued under the UK SFLG public loan guarantee scheme over the period 2000 to 2005 and were provided by the UK Department for Business Innovation and Skills (DBIS). Other works have previously exploited the dataset in its previous releases (see Cowling and Mitchell, 2003 and Cowling, 2010) and in its current form (see

Cowling and Siepel, 2013 and Ughetto et al., 2017). The initial dataset includes 31,434 guarantee backed loans issued between 2000 and 2005 by 25 financial institutions in the UK (of which 80% are issued by Barclays Bank Plc, National Westminster Bank plc, Lloyds Bank plc, HSBC Bank Plc, i.e. the four major UK banks).

After we dropped observations reporting missing values and outliers in the main computed variables, we ended up with a final sample consisting of 29,266 SFLG backed loans. To identify high-tech firms we searched the 4 digit SIC codes for each firm and applied the Eurostat classification based on Rev. 2 NACE 2-digit level codes to the corresponding SIC codes. Similarly to other previous works (e.g. Benfratello et al., 2008; Himmelberg and Petersen, 1994; Ughetto, 2008; Ughetto et al. 2017), high-tech firms are those operating in the following manufacturing sectors: computer, electronic and optical products; chemicals and drugs; electrical equipment; mechanical machinery; transportation equipment[2].

To test the differential impact on the cost of debt and on the probability of default that loans issued to high-tech firms might have when different regional conditions apply, we searched for economic data on UK regions. The UK Competitiveness Index (year 2005), provided by the Centre for International Competitiveness, was used to distinguish between developed and lagging regions[3]. To measure the level of financial development of the local credit markets, we collected data on the regions' number of bank branches from Eurostat-Regio (year 2003) and constructed a measure of bank branch density (number of branches divided by population), as it was done in previous studies (see, for instance, Benfratello et al., 2008; Ughetto et al., 2017). Financially developed regions have been defined as regions with a bank branch density higher than the median. Data on the total number of firms in the different SIC sectors in UK regions were extracted from the Office of National Statistics (2005). We then applied the Eurostat classification on High-tech industry to identify high-tech sectors and calculated the number of firms in the high-tech sector (as a percentage of total firm population) for

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[2] http://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an3.pdf

[3] Such index is a composite indicator based on: 1) input factors (i.e. R&D expenditure, economic activity rates, business start-up rates per 1,000 inhabitants, number of businesses per 1,000 inhabitants, proportion of working age population with NVQ level 4 or higher, proportion of knowledge based businesses), (2) output factors (i.e. value added per head at current basic prices, exports per head of population, imports per head of population, productivity-output per hour worked, employment rates) and (3) outcome factors (gross weekly pay, unemployment rates).

each UK region to define technologically advanced regions. We also collected from Eurostat-Regio data on labour cost, wages and salaries and direct remuneration per hour per employee and number of firms younger than 3 years (as a percentage of total firm population) to identify high labor cost regions and young firm regions.

In our empirical analysis we employ two dependent variables in the IV OLS and probit models respectively: (1) the spread, our measure of the price of lending, defined as the bank margin over base deflated by price index, and (2) the default, a dummy variable equal to 1 if the loan defaults and 0 otherwise. Spreads are on average around 3.12%, although they can peak at much larger values. Out of 29,266 loans issued, nearly 28% ended in default. The typical firm in our sample receives a loan of the average amount of £63,937 (but loans can reach higher amounts up to £250,000). Guarantee backed loans are issued mainly to cover working capital needs (56.5%). Descriptive statistics show that more than half of the firms' total amount of financial debt is covered by the public guarantee (58%), although this percentage can rise up to a maximum of 85%. It has to be noted that the share of publicly guaranteed debt is fixed and determined by the policy scheme (in Phase VI, the Government coverage is 70% of the loan amount for firms with less than two years and 85% for older borrowers and in Phase VII it is 75%), so that the variation of the "guarantee coverage" is driven by the relative incidence of the guaranteed loan with respect to the amount of the other financial debt.[4]

We also know that firms have overdraft facility outstanding in 37.1% of the cases. Firms applying for a guarantee backed loan are mostly micro and small-sized enterprises, reporting an average turnover of £0.35 million. High-tech firms represent the 10.4% of the sample. 59.8% of the firms are located in financially developed regions, 40.8% in developed regions, 41.4% in technologically advanced regions, 45.4% in high labour cost regions and 49.6% in young firm regions.

[4] In fact, the variable "guarantee coverage" is defined as the ratio between the amount of the loan covered by the public guarantee and the total amount of outstanding loans (included the amount of financial debt, provided by any eligible bank in the UK, that a firm has in addition to the guarantee-backed debt). This variable is influenced by the interplay of the policy initiative and the previous demand/supply for banks loans, which might reflect unobservable firm-level factors.

A listing of the variables used in the empirical analysis along with their definitions and their descriptive statistics (mean, median, standard deviation) is provided in Table 1.

[Insert Table 1 here]

4. Empirical analysis

In this section we first present a set of Instrumental variable (IV) OLS regressions (Table 2) in which the dependent variable is the spread (the adjusted loan interest rate). Instrumental variable regressions allow us to control for potential endogeneity problems (Wooldridge, 2002). The endogeneity problems attain the variable guarantee coverage, which might be affected, as it happens for the loan spread, by firm riskiness and other unobservable exogenous shocks. The variables start-up and turnover are used as instrumental variables for guarantee coverage. Table 2 reports the Wu–Hausman test for endogeneity. The null hypothesis is that guarantee coverage can be treated as exogenous. The Wu–Hausman test statistics are significant in all model specifications, suggesting a rejection of the null of exogeneity. The choice of these two instrumental variables is supported by the Basmann test of overidentifying restrictions[5].

A more comprehensive picture of the determinants of the spread can be obtained by using quantile regressions (reported in the Appendix). While OLS regression focuses on the mean of the dependent variable, quantile regressions model the relationship between a set of regressors and the percentiles (Koenker and Bassett, 1978; Mosteller and Tukey, 1977). In our specific case, the quantile regression estimates the change in a specified quantile of the spread produced by a one unit change in an explanatory variable. This allows us to compare how some percentiles of the spread distribution may

[5] The exogeneity condition implies that at least one instrument must be exogenous. The exogeneity of the instrument "start-up" can be justified from a theoretical point of view, referring to the specific context of the SFLG scheme. Indeed, the variable start-up is negatively correlated with the variable guarantee coverage because start-ups do not usually have previous debt, but is unrelated to the outcome (spread). This is possible because the SFLG Scheme is financing young firms aged between 0 and 5 years old. While it can be expected that firm age has a non negligible effect on the spread in a sample of firms characterized by a large variance of firm age, this is not the case with our specific sample. Indeed, it might be argued that in the specific SFLG Scheme context, interest rates are charged based upon other unobservable firm-related factors (e.g. such as the quality of the business plan).

be more affected by certain loan and firm characteristics more than other percentiles, a particular concern because of the potentially skewed distribution of risk amongst high-technology firms. To tackle the previously mentioned endogeneity problem, we run IV quantile regressions, using a relatively new method and coding (i.e. ivqreg routine for Stata developed by Kwak, 2010). The variables start-up and turnover are used as instrumental variables for guarantee coverage.

We then run a set of probit models to predict the probability of loan default (Table 3). High-tech is our main variable of interest. The aim of the analysis is to study the loan pricing conditions and the probability of loan default for high-tech applicants. We are also interested in identifying specific differential patterns when high-tech firms are located in regions with different levels of economic, financial and technological development and when different macro-economic conditions and types of lenders apply. We therefore interact the dummy variable high-tech with a number of variables identifying regional and economic dimensions. Independent variables include the amount of the loan covered by the guarantee scheme as a percentage of the total amount of outstanding loans, firm and loan characteristics. We also control for sectors, regions, banks and macro-economic conditions.

Table 2 reports the econometric analysis of the determinants of the spread through IV OLS regressions. Model 1 illustrates the baseline specification that includes among the regressors a set of basic loan (i.e. guaranteed coverage, loan amount, additional loan commitments, loan purpose) and firm level variables (i.e. company status, high-tech). The main variable of interest for the purpose of the study is whether firms belong to the high-tech sector. We control for region dummies and macro-economic conditions (GDP growth). We then augment this specification by including interaction variables equal to the dummy high-tech times dummy variables on whether the loan was granted by the biggest four UK banks (model 2) and in recession times (model 3). The high-tech dummy variable is then interacted with a number of variables identifying whether loan applicants are located in economically and financially developed regions (models 4 and 5), technologically advanced regions (model 6), high labor cost regions (model 7) and regions with a large population of young firms (model 8).

Results in Table 2 indicate that the higher is the incidence of the publicly guaranteed debt over the total amount of outstanding loans, the lower is, on average, the spread[6]. Higher margins are charged for loans issued for working capital purposes and in periods of economic growth. Higher rates are also applied for limited partnerships/companies and by the biggest four UK banks, although this effect loses statistical significance in models 5 and 7.

High-tech firms are charged, on average, higher rates on loans. This result is significant at 1% level of statistical significance in all model specifications. This is in line with the expectation that high-tech firms face a greater cost premium for the use of external finance because of their limited availability of collateral to secure firms' borrowing and the high degree of risk which characterizes the returns of R&D investments.

We find evidence that the public loan guarantee scheme is successful in reducing the cost of debt for firms located in economic and financially developed regions, technologically developed, high labor costs and young firm regions. In these regions loan applicants are charged, on average, lower spreads. It is in fact plausible that more creditworthy firms populate these areas because of the greater opportunities they receive in terms of access to credit, infrastructures and business networks, leading banks to apply lower margins on their loans. However, it is also the case that closer proximity to small business customers lowers information asymmetries. In addition, there is the potential for financial institutions in more developed financial markets to invest more in information processing systems to support lending. Finally, there is a more textbook competition effect on prices in that greater competition for loans from the supply side reduces prices in the market.

[6] In a previous work (Ughetto et al., 2017), we investigated for which type of borrowers and loans does the public guarantee generate a more favorable effect (in terms of reduction in the cost of capital). We found that an increase of the incidence of the debt guaranteed by government with respect to the total outstanding debt leads to a contraction in the spread only for loans covering working capital needs rather than investments. However, we did not find any differential impact when the sample is split according to whether borrowers belong to high-tech or low-tech manufacturing sectors and to knowledge-intensive or less knowledge-intensive service sectors.

From a public policy perspective, it is interesting to examine whether differential patterns on the spread charged to high-tech firms differ by regional and economic context. We find positive and significant coefficients for the interactions between the variable high-tech and the binary variables identifying the regions characterized by high levels of labor cost (model 7) and economic development (model 4) and technological advances (model 6). Hence, the impact on the spread for firms belonging to the high-tech sector is larger if they are located in high labor cost, technologically advanced and developed regions[7]. The interaction effect is not significant when high-tech firms receive their loans from the biggest 4 UK banks and when they are located in financially developed regions or in regions with a large population of young firms. Results also indicate that lower margins are applied in states of a bad economy and that this holds true for high-tech firms.

[Insert Table 2 here]

The IV quantile regression results in Table 1A show that the IV OLS estimates do not tell the whole story. The value of the estimated coefficients for the variable high-tech seems to vary over the spread distribution, with the highest coefficients at the median (50th percentile). When interactions are considered, the negative association between the spread and the interaction variable high-tech*recession is significant at both 25th and 50th percentiles, but it is not significant at the 75th percentile. The impact on the spread for high-tech firms located in developed regions is larger for higher percentiles of the spread (75th percentiles). A positive and significant correlation between the spread and the interaction variable high-tech*high-tech region is only found at the 75th percentile. At all percentiles the variable 'high-tech * high labor cost region displays a positive and statistically significant effect on the spread, showing a bigger effect in the 50th and 75th percentiles. The coefficients for loans issued to cover working capital needs and for guaranteed coverage are larger at the 75th percentiles, and the latter is not significant at the lowest quantiles.

[7] We also experimented with alternative variables concerning the technological development of a region, such as if the firm is located in a region with total R&D personnel in head count in percentage of active population greater than the sample median and in a region with employment in technology and knowledge intensive sectors greater than the sample median. Results are in line with those reported in Model 6 of Table 2.

In Table 3 we run a simple probit model on the probability that the loan ends in default. Understanding what drives default and what is the probability that loans received by high-tech firms end in default and how this varies when different time and local conditions apply is crucial for an assessment of the cost to government of running the scheme. The default rate for the total population of SFLG loans over the period 2000-2005 is 28% and this percentage rises to 36% for the sub-sample of high-tech firms. The dependent variable of the probit model is default, which is a binary outcome coded 1 if the loan ended in default and zero otherwise. Independent variables are the same reported in previous IV OLS regressions.

We observe that firms with higher turnover show, on average, lower default rates. Loans used for working capital purposes on average have higher default rates, and this effect is significant at 1% level. The increase in the likelihood of default due to marginal increases in the variable loan wc is approximately 9.8%. In contrast, no relationship is found between loan amount and default. The relationship between the guarantee coverage and subsequent default is not statistically significant. As expected, in recessionary times the probability of default is greater than in good states of the economy. Interestingly, firms located in economically developed, technologically advanced and young firm regions are more likely to default, while firms located in financially advanced regions are the least likely to default.

The key finding from the default model is that there is a positive relationship between high-tech applicants and subsequent default. This result is significant at 1% level and robust in almost all model specifications (with the exception of model 7). Being a high-tech firm increases the default probability by approximately 5%, depending on the considered model (from the lowest 3% to the highest 7%). Interaction effects in the probit model show a negative and significant correlation with the default probability for the interacted variables high-tech*big4, high-tech* developed region, high-tech* high-tech region and high-tech*young firm region, while high-tech* financially developed region displays a positive and significant correlation with the dependent variable. Looking at the magnitude of the interaction effects[8], it emerges that high-tech firms are 3.7% more likely to default if the loan is not provided by the biggest four banks. Instead, loans provided to high-tech firms from one of the four biggest UK banks have a comparatively lower probability to default (even if, on average, such loans are associated with higher default rates). In fact, the probability of default decreases by 1.2% when high-tech firms are financed by the major four UK banks. This effect is significant at 5% significance level. For high tech firms belonging to financially developed regions the probability of default is 10.6% higher, while firms not belonging to a financial developed region are 7.3% more likely to default (at 1% level of statistical significance). It also emerges that high-tech firms operating in economically advanced and young firm regions are 1.2% more likely to default, but this effect is not statistically significant. The likelihood of default decreases by 0.8% for firms operating in high-tech regions but again this effect is not statistically significant.

[Insert Table 3 here]

5. Conclusions

We have explored in depth several key questions relating to small business lending in the context of high-technology firms under a prominent UK publicly guaranteed scheme. In particular, we questioned; (a) whether high-technology firms are a greater lending risk, (b) whether technology firms face an additional loan price premium over and above that relating to their smallness (the innovation penalty), (c) whether the presence of a government backed loan guarantee alters banks view in respect of their loan risk-premium, (d) whether spatial location of the firm in the context of the specific regional economic, innovation, and competitive position alters the way banks price lending to technology firms.

Firstly, we found clear evidence that high-technology firms present a higher default risk to banks with loan default being observably higher than that of conventional firms. But the difference in

[8] As pointed out by Ai and Norton (2003) the magnitude of the interaction effect in nonlinear models does not equal the marginal effect of the interaction term.

predicted loan default probabilities for high-technology firms was not particularly large, suggesting that they are not as risky as might be commonly perceived. In relation to the price of lending, our core finding was that there is evidence of an 'innovation premium' on lending to high-technology firms. But this was only in the region of 0.5-0.6% which suggests that the actual magnitude of the 'innovation premium' is not particularly large in the presence of a substantial guarantee coverage rate. Further, it was the case that the provision of the public loan guarantee lowered interest spreads significantly for all firms.

In general, we found that banks penalize short-term lending, particularly for working capital. This suggests that cash-flow problems and the inability to self-finance working capital from retained earnings is viewed as a poor signal by lending banks. In periods of economic growth, banks also appear to take advantage of firms relative lack of price sensitivity and charge higher loan rates. In line with what standard economic models of imperfect markets predict, the big-4 UK banks lend at higher rates than their smaller counterparts. When combined with their ability to raise cheap capital on international markets, and their ability to extract surplus profits from non-lending related activities from customer firms, small firm lending for bigger banks is likely to be substantially more profitable.

We found evidence of spatial variation in both the cost of loans to high-technology firms and their default rates, although our evidence is relatively nuanced. At a general level, lending is cheaper in economically developed regions, in regions with highly developed financial markets, in regions where there is a significant high-technology cluster and presence, and in regions characterized by a young and dynamic business sector. But these benefits are not shared equally across all firms. In particular, high-tech firms still face a debt penalty in economically developed regions, in technologically advanced regions and in high wage (labor cost) regions. This might suggest that when banks have a large demand for loans from conventional, lower-risk, firms, then the need to expand their lending to high-tech firms incurs a penalty, even when the regional economy is buoyant and technologically fervent.

However, it was also interesting to note that high-tech firms faced no penalty in regions with well-developed financial markets. This suggests competition on the supply-side of the loan market drives general debt prices downwards. In short, when a firm has many alternatives when seeking finance, banks react by lowering their price to be more attractive to potential borrowers.

The study has some clear limitations, which mainly involve the typology of data at disposal. First, we cannot control for the economic and financial standing of our sample firms, because they are to a large extent small and young companies that in the UK are exempt, by law, from full financial reporting. We made such check with the FAME dataset and found just a small number of them. Another limitation relates to the lack of information on the seniority of the credit lines, which would have allowed further refinements of the analysis.

Focusing on the public policy implications of our findings, our data reveal that, on average, high-tech firms still face a modest innovation debt penalty even when lending in the context of a policy measure that should, in principle, lower the cost of lending to firms facing significant financing gaps. What is clear is that high-tech firms are not treated the same as their more conventional peers when lending and this general feature can be exacerbated by spatial differences in economics, innovation, and competitiveness.

In terms of identifying some practical implications for policy-makers, banks, and technology entrepreneurs, our evidence suggests some areas for consideration and development. For policy-makers, there is an interesting tension between the provision of a standardized national loan guarantee scheme which is well understood by all market participants and a more segmented approach to the design of schemes which takes greater account of the more specific aspects of financing particularly types of firms and local economic and financial systems. But this latter approach would add complexity at the operational level and risks creating small, less effective, sub-national funds (Nightingale et al., 2009). For banks, our evidence suggests an implication that has great relevance to their general lending processes and in terms of administering a loan guarantee scheme. It would appear that larger banks, those with more sophisticated loan processing systems, are better able to price loans according to true risk, and this feature is enhanced when they are operating in more sophisticated, and competitive, financial markets. But this must be considered against the overall firm environment in which high-tech firms are only moderately more of a default risk than more conventional firms. For entrepreneurs, a better understanding of how banks price loans might support better prepared loan applications, particularly when there is an opportunity to offer soft, as well as hard information to potential financiers.

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Tables

Table 1-Descriptive statistics (mean, median, standard deviation) and definitions of the variables used in the empirical analysis

	Definition	Mean	Median	SD
spread	Bank margin over base deflated by price index	3.126	2.6	2.087
default	A dummy variable equal to 1 if the loan defaults and 0 otherwise	0.280	0	0.265
guarantee coverage	Ratio between the amount of the loan covered by the guarantee scheme and the total amount of outstanding loans (in £)	0.580	0.7	0.229
overdraft	A dummy variable equal to 1 if the firm has additional overdraft outstanding and 0 otherwise	0.371	0	0.483
loan wc	A dummy variable equal to 1 if the loan is issued to cover working capital needs and 0 otherwise	0.565	1	0.495
loan amount	Loan amount (in million £)	0.063	0.05	0.052
limited	A dummy variable equal to 1 if the firm is a limited partnerhip/company and 0 otherwise	0.709	1	0.454
turnover	Firm's turnover (in million £)	0.345	0.14	0.505
start-up	A dummy variable equal to 1 if the firm is a start-up and 0 otherwise	0.295	0	0.456
high-tech	A dummy variable equal to 1 if the firm belongs to the high-tech sector (SIC classification) and 0 otherwise	0.104	0	0.305
big4	A dummy variable equal to 1 if the firm's main loan is issued by one of the four major UK clearing banks and 0 otherwise	0.801	1	0.399
GDP growth	Quarterly GDP growth	0.597	0.54	0.269
recession	A dummy variable equal to 1 if the economy is in recession and 0 otherwise	0.203	0	0.402
developed region	A dummy variable equal to 1 if the firm is located in a developed region (with a UK competitiveness Index higher than the median) and 0 otherwise	0.408	0	0.491
financially developed region	A dummy variable equal to 1 if the firm is located in a financially developed region (with a bank branch density higher than the median) and 0 otherwise	0.598	1	0.490
high-tech region	A dummy variable equal to 1 if the firm is located in a region with a number of firms in the high-tech sectors as a percentage of total firm population greater than the sample median and 0 otherwise	0.414	0	0.492
high labour cost region	A dummy variable equal to 1 if the firm is located in a region with labour cost, wages and salaries and direct remuneration per hour per	0.454	0	0.497

	employee greater than the sample median and 0 otherwise			
young firm region	A dummy variable equal to 1 if the firm is located in a region with a number of firms younger than 3 years as a percentage of total firm population greater than the sample median and 0 otherwise	0.496	0	0.499

Table 2. Instrumental variable (IV) OLS regressions. Dependent variable: spread

	Model	Model	Model	Model	Model	Model	Model	Model
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
guarantee coverage	-3.073**	-3.071**	-3.320**	-3.140**	-3.227**	-3.016**	-3.195**	-3.197**
	(1.316)	(1.325)	(1.359)	(1.321)	(1.307)	(1.311)	(1.306)	(1.314)
limited	0.168***	0.168***	0.181***	0.172***	0.175***	0.169***	0.173***	0.171***
	(0.031)	(0.031)	(0.032)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
overdraft	-0.176	-0.176	-0.164	-0.185	-0.196	-0.170	-0.192	-0.193
	(0.178)	(0.179)	(0.185)	(0.179)	(0.177)	(0.177)	(0.177)	(0.178)
loan wc	0.333***	0.333***	0.322***	0.339***	0.340***	0.338***	0.340***	0.339***
	(0.026)	(0.026)	(0.027)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
loan amount	-0.027	-0.026	-0.387	-0.139	-0.127	-0.152	-0.149	-0.100
	(0.910)	(0.914)	(0.947)	(0.929)	(0.926)	(0.922)	(0.924)	(0.925)
high-tech	0.548***	0.521***	0.654***	0.482***	0.504***	0.476***	0.447***	0.505***
	(0.044)	(0.082)	(0.050)	(0.054)	(0.070)	(0.053)	(0.062)	(0.059)
growth_GDP	2.160***	2.160***		2.161***	2.161***	2.163***	2.161***	2.160***
	(0.052)	(0.052)		(0.052)	(0.052)	(0.052)	(0.052)	(0.052)
big4	0.184***	0.180***	0.134***	0.057*	0.021	0.071**	0.024	0.066**
	(0.040)	(0.041)	(0.041)	(0.033)	(0.034)	(0.033)	(0.034)	(0.033)
high-tech*big4		0.036						
		(0.099)						
recession			-0.731***					
			(0.033)					
high-tech*recession			-0.278***					
			(0.099)					
developed region				-0.098***				
				(0.029)				
high-tech*developed region				0.161**				
				(0.081)				
financially developed region					-0.070***			
					(0.027)			
high-tech*financially developed region					0.069			
					(0.083)			
high-tech region						-0.170***		
						(0.028)		
high-tech*high-tech region						0.179**		
						(0.082)		
high labour cost region							-0.063**	

							(0.026)	
high-tech*high labour cost region							0.202**	
							(0.080)	
young firm region								-0.099***
								(0.028)
high-tech*young firm region								0.086
								(0.079)
Region dummies	yes	yes	no	no	no	no	no	no
Constant	3.600***	3.602***	5.161***	3.367***	3.449***	3.310***	3.415***	3.403***
	(0.823)	(0.825)	(0.834)	(0.775)	(0.765)	(0.768)	(0.767)	(0.771)
Observations	29,266	29,266	29,266	29,266	29,266	29,266	29,266	29,266
Wald chi2	3416.08***	3417.88***	3287.65***	3281.94***	3251.07***	3340.23***	3256.55***	3269.85***
Wu–Hausman test of endogeneity	4.660**	4.586**	4.983**	4.823**	5.259**	4.449**	5.132**	5.095**
Basmann test of overidentifying restrictions	1.909	1.926	1.118	1.784	1.494	2.175	1.596	1.716

Note: The Table reports the Instrumental variable OLS regressions to test the determinants of the spread. Instrumented: guarantee coverage. The variables start-up and turnover are used as instrumental variables for guarantee coverage. The definitions of the independent variables are provided in Table 1. For the sake of synthesis, we omit estimated coefficients for region dummies. The Table reports Wu–Hausman test of endogeneity and Basmann test of overidentifying restrictions. Robust standard errors are in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table 3. Probit model. Dependent variable: loan default (coefficients reported)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Model	Model	Model	Model	Model	Model	Model	Model
guarantee coverage	0.048	0.048	0.048	0.047	0.047	0.049	0.048	0.048
	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)
overdraft	-0.002	-0.002	-0.001	-0.000	-0.002	-0.001	-0.001	-0.001
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
loan wc	0.301***	0.302***	0.302***	0.301***	0.301***	0.301***	0.300***	0.302***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
loan amount	0.052	0.048	0.041	0.052	0.035	0.065	0.067	0.033
	(0.177)	(0.177)	(0.176)	(0.176)	(0.177)	(0.176)	(0.175)	(0.176)
turnover	-0.188***	-0.188***	-0.187***	-0.188***	-0.187***	-0.188***	-0.190***	-0.187***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
high-tech	0.093***	0.111***	0.150***	0.163***	0.214***	0.132***	0.033	0.154***
	(0.026)	(0.029)	(0.033)	(0.034)	(0.052)	(0.036)	(0.041)	(0.036)
big4	0.046*	0.045*	0.073***	0.078***	0.066**	0.083***	0.075***	0.066***
	(0.027)	(0.027)	(0.021)	(0.021)	(0.028)	(0.021)	(0.021)	(0.021)
high-tech*big4					-0.158***			
					(0.059)			
recession		0.102***						
		(0.023)						
high-tech*recession		-0.087						
		(0.061)						
developed_region			0.047***					
			(0.018)					
high-tech* developed region			-0.140***					
			(0.051)					
financially developed region							-0.037**	
							(0.017)	
high-tech* financially developed region							0.097*	
							(0.052)	
high-tech region				0.037**				
				(0.018)				
high-tech* high-tech region				-0.166***				
				(0.051)				
high labor cost region						0.021		
						(0.017)		
high-tech* high labor cost region						-0.081		
						(0.050)		
young firm region								0.060***
								(0.018)
high-tech*young firm region								-0.126**
								(0.050)
Constant	-1.515***	-1.539***	-1.303***	-1.303***	-1.536***	-1.302***	-1.261***	-1.308***
	(0.104)	(0.104)	(0.039)	(0.039)	(0.104)	(0.040)	(0.041)	(0.039)
Observations	29,266	29,266	29,266	29,266	29,266	29,266	29,266	29,266
Pseudo R-squared	0.049	0.050	0.049	0.049	0.049	0.049	0.049	0.049

Note: The Table reports the probit models to test the probability of loan default (coefficients reported). The definitions of the independent variables are provided in Table 1. For the sake of synthesis, we omit estimated coefficients for region dummies. Robust standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.10.

Appendix

Table 1A (panel a). IV Quantile regressions. Dependent variable: spread

	Model 1			Model 2			Model 3		
	25perc	50perc	75perc	25perc	50perc	75perc	25perc	50perc	75perc
guarantee coverage	1.069	-4.486***	-6.831***	2.245***	-5.809***	-8.418***	0.735	-3.562**	-8.384***
	(1.047)	(1.554)	(2.436)	(1.676)	(1.586)	(2.207)	(0.863)	(1.496)	(2.315)
overdraft	0.229	-0.320	-0.470	0.425**	-0.371*	-0.673**	0.176	-0.180	-0.676**
	(0.141)	(0.210)	(0.330)	(0.226)	(0.215)	(0.300)	(0.116)	(0. 202)	(0.313)
loan wc	0.137***	0.410***	0.622***	0.128***	0.438***	0.599***	0.113***	0.424***	0.651***
	(0.020)	(0.030)	(0.048)	(0.021)	(0.031)	(0.044)	(0.016)	(0.029)	(0.046)
loan amount	-1.487**	0.683	1.432	-2.497***	0. 994	1.711	-1.194**	-0.171	2.091
	(0.723)	(1.071)	(1.667)	(1.142)	(1.105)	(1.525)	(0.606)	(1.052)	(1.615)
limited	0.046**	0.213***	0.296***	0.013	0.239***	0.360***	0.038**	0.222***	0.324***
	(0.023)	(0.035)	(0.056)	(0.027)	(0.036)	(0.051)	(0.019)	(0.034)	(0.053)
high-tech	0.508***	0.805***	0.546***	0.732***	0.946***	0.611***	0.418***	0.793***	0.515***
	(0.063)	(0.096)	(0.151)	(0.040)	(0.057)	(0.081)	(0.034)	(0.061)	(0.095)
growth_GDP	2.301***	2.465***	2.041***				2.300***	2.479***	1.991***
	(0.038)	(0.060)	(0.093)				(0.032)	(0.058)	(0.088)
big4	0.043	0.180***	0.359***	-0.007	0.074	0.341***	-0.024	0.053	0.117**
	(0.032)	(0.048)	(0.075)	(0.034)	(0.048)	(0.066)	(0.021)	(0.037)	(0.057)
high-tech*big4	-0.004	0.019	0.150						
	(0.076)	(0.115)	(0.181)						
recession				-0.491***	-0.639***	-1.042***			
				(0.024)	(0.038)	(0.053)			
high-tech*recession				-0.508***	-0.305***	-0.150			
				(0.075)	(0.115)	(0.163)			
developed region							-0.042**	-0.104**	-0.176***
							(0.018)	(0.033)	(0.051)
high-tech*developed region							0.084*	0.166**	0.301**
							(0.051)	(0.091)	(0.141)
Region dummies	yes	yes	yes	yes	yes	yes	no	no	no
Constant	-0.460	3.327***	6.261***	0.323	5.782***	8.803***	-0.215	2.867***	7.423***
	(0.618)	(0.918)	(1.442)	(0.971)	(0.921)	(1.283)	(0.506)	(0.877)	(1.359)
Observations	29,266	29,266	29,266	29,266	29,266	29,266	29,266	29,266	29,266

Table 1A(panel b). IV Quantile regressions. Dependent variable: spread

	Model 4			Model 5			Model 6			Model 7		
	25perc	50perc	75perc	25perc	50perc	75perc	25perc	50perc	75perc	25perc	50perc	75perc
guaranteed_coverage	0.862	-3.880**	-8.307***	0.725	-4.397***	-7.674***	0.508	-4.034***	-8.405***	0.687	-3.908***	-8.629***
	(0.854)	(1.535)	(2.410)	(0.851)	(1.401)	(2.310)	(0.921)	(1.525)	(2.279)	(0.826)	(1.407)	(2.277)
overdraft	0.193*	-0.220	-0.675**	0.177	-0.299	-0.574**	0.145	-0.241	-0.667**	0.169	-0.231	-0.702**
	(0.115)	(0.207)	(0.326)	(0.114)	(0.189)	(0.312)	(0.124)	(0.206)	(0.308)	(0.111)	(0.190)	(0.308)
loan wc	0.114***	0.428***	0.640***	0.117***	0.421***	0.657***	0.108***	0.428***	0.652***	0.113***	0.428***	0.648***
	(0.016)	(0.030)	(0.048)	(0.016)	(0.027)	(0.046)	(0.018)	(0.030)	(0.046)	(0.016)	(0.028)	(0.045)
loan amount	-1.358**	0.092	1.877	-1.195**	0.378	1.639	-1.028	0.191	1.953	-1.170**	0.131	2.229
	(0.604)	(1.087)	(1.693)	(0.598)	(0.986)	(1.613)	(0.651)	(1.078)	(1.599)	(0.582)	(0.991)	(1.591)
limited	0.036**	0.224***	0.341***	0.042**	0.219***	0.338***	0.039**	0.224***	0.335***	0.037**	0.220***	0.334***
	(0.019)	(0.035)	(0.056)	(0.019)	(0.032)	(0.054)	(0.021)	(0.035)	(0.053)	(0.019)	(0.032)	(0.053)
high-tech	0.533***	0.709***	0.460***	0.477***	0.792***	0.470***	0.415***	0.670***	0.474***	0.486***	0.820***	0.550***
	(0.045)	(0.082)	(0.130)	(0.034)	(0.057)	(0.095)	(0.042)	(0.072)	(0.108)	(0.036)	(0.063)	(0.102)
growth_GDP	2.302***	2.488***	1.983***	2.293***	2.451***	2.003***	2.303***	2.467***	1.988***	2.300***	2.463***	1.994***
	(0.032)	(0.061)	(0.093)	(0.032)	(0.055)	(0.089)	(0.035)	(0.060)	(0.088)	(0.031)	(0.055)	(0.088)
big4	-0.047**	0.027	0.051	-0.017	0.075**	0.150***	-0.035	0.027	0.068	-0.019	0.074**	0.123**
	(0.021)	(0.039)	(0.062)	(0.021)	(0.035)	(0.057)	(0.023)	(0.039)	(0.059)	(0.020)	(0.035)	(0.057)
financially developed region	-0.038**	-0.087***	-0.155***									
	(0.017)	(0.031)	(0.049)									
high-tech*financially developed region	-0.037	0.245**	0.270*									
	(0.053)	(0.097)	(0.154)									
high-tech region				-0.068***	-0.175***	-0. 346***						
				(0.018)	(0.030)	(0.050)						
high-tech*high-tech region				0.079	0.130	0. 436***						
				(0.052)	(0.087)	(0.145)						
high labor cost region							-0.009	-0.079***	-0.145***			
							(0.018)	(0.030)	(0.045)			
high-tech*high labor cost region							0.182***	0.341***	0.336***			
							(0.055)	(0.093)	(0.140)			
young firm region										-0.046***	-0.113***	-0.152***
										(0.017)	(0.030)	(0.049)
high-tech*young firm region										0.067	0.060	0.153
										(0.049)	(0.084)	(0.137)
Constant	-0.260	3.068***	7.463***	-0.203	3.399***	7.020***	-0.088	3.155***	7.463***	-0.184	3.073***	7.558***

	(0.500)	(0.899)	(1.412)	(0.498)	(0.821)	(1.355)	(0.540)	(0.895)	(1.339)	(0.484)	(0.825)	(1.337)
Observations	29,266	29,266	29,266	29,266	29,266	29,266	29,266	29,266	29,266	29,266	29,266	29,266

Note: The Table reports the IV quantile regressions (25 perc, 50 perc, 75 perc) to test the determinants of the spread. IV quantile regressions are run using the Stata ivqreg routine developed by Do Won Kwak (2010). Instrumented: guarantee coverage. The variables start-up and turnover are used as instrumental variables for guarantee coverage. The definitions of the independent variables are provided in Table 1. For the sake of synthesis, we omit estimated coefficients for region dummies. Robust standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.10.

Table 2A. Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
guarantee coverage (1)	1											
overdraft (2)	0.0714	1										
loan wc (3)	0.0947	0.022	1									
loan amount (4)	-0.0596	-0.0075	-0.0131	1								
limited (5)	0.0137	0.0067	-0.1022	0.1939	1							
big4 (6)	-0.0062	-0.0042	-0.0113	-0.1148	0.018	1						
growth GDP (7)	0.2922	0.041	-0.0022	-0.0432	0.0013	-0.0347	1					
hightech (8)	0.1005	0.0351	0.1275	0.0769	0.0317	-0.0365	0.0182	1				
recession (9)	-0.147	-0.0038	-0.004	0.0021	-0.0013	0.0166	-0.5421	0.0089	1			
high labour cost region (10)	-0.0156	-0.016	0.0038	0.0524	-0.0038	-0.2053	-0.0129	0.0401	0.005	1		
young firm region (11)	-0.0358	-0.0094	-0.0226	0.0196	0.0025	0.2856	-0.0258	0	0.0066	0.4314	1	
high-tech region (12)	-0.0486	-0.0125	-0.0208	0.0629	0.011	0.2079	-0.0218	0.015	0.0063	0.5896	0.5151	1
financially developed region (13)	-0.0219	-0.0076	-0.0045	0.0251	0.0138	-0.1737	-0.0126	0.0165	0.007	0.3536	-0.2466	-0.0468
developed region (14)	-0.0354	-0.012	-0.0242	0.0371	0.0149	0.2422	-0.0286	0.0072	0.0076	0.6021	0.8369	0.6747